EFFECTS OF HUMAN DECISION BIAS ON SUPPLY CHAIN PERFORMANCE

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EFFECTS OF HUMAN DECISION BIAS ON SUPPLY CHAIN PERFORMANCE

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To my father

who selflessly provides for his family.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

SUMMARY

This dissertation studies the bias in newsvendor (NV) decision-making and its effect on the performance of NV supply chain. Studies in NV decision-making have shown human decisions to systematically deviate from the profit maximizing solutions of various utility models. Yet for the most part the impacts of this human decision bias in systems of newsvendor type products have not been investigated. NV's initial wealth and alternative NV requisition policies are proposed as sources of human decision bias.

Effects of individual's initial wealth on NV decision-making are analyzed in risk-aversion and loss-aversion NV utility models. Analysis of the risk-averse utility model reveals conflicting effects of NV's initial wealth on NV decision-making due to different Arrow-Pratt measures of absolute risk-aversion. The analysis of loss-averse utility model predicts wealthier NV to order more than poorer NV under a maximum undesirable wealth assumption.

Effects of various competing newsvendor requisition policies are analyzed in a human decision bias (HDB) model. The HDB model facilitates the comparative analysis of individual decision-making in various conditions of NV systems. This model also identifies the anchoring and adjustment effect in the single NV context. A multi-echelon version of HDB model shows NV supplier's reliance of demand chasing heuristics in the multi-echelon NV context. The HDB model is expected to improve NV supply chain design by accounting for human decision bias.

Hypotheses of the effects of NV's initial wealth and alternative NV requisition policies on individual NV decision-making are empirically tested in single and multi-echelon NV experiments. More than 9000 NV decisions from 171 student subjects collected over a span of more than 6 months were analyzed in various statistical methods.

Statistical analyses of single NV experiments support the hypotheses of decreasing absolute risk aversion (DARA) and loss-aversion. Factorial experiment analysis results show NV's initial wealth term and item profit margin term to significantly affect NV decision-making. Regression analyses fail to reject hypotheses of dominant alternative NV requisition policies to the EOQ policy. The statistical analyses of multi-echelon NV experiment found item profit margin, NV's initial wealth, and relationship between supplier and retailer to significantly affect newsvendor decision-making.

Finally, the performance of NV systems suffers as a result of human decision bias. The empirical evidences of all NV experiments show that human decision bias reduces the profitability in both the single and the multi-echelon settings. A hypothetical case study of an organic food manufacturer further illustrates how human decision bias affects the optimal solution of a supply chain design and reduces overall supply chain profit. We believe this research has advanced the theory of human decision bias in the NV supply chain systems.

CHAPTER 1: INTRODUCTION

Consider a newsvendor who has only one opportunity in the morning to decide how many newspapers to order to satisfy the day's demand. If he orders too much, his cost will be too high. If he orders too little, he will miss out on additional profit. This practical and well studied problem is often called the single period newsvendor problem (SPP). The objective of SSP is to identify an order quantity that will balance the costs of ordering too little, a.k.a. stock out costs and the costs of ordering too much, a.k.a. overage costs.

SPP is a foundational paradigm of the research in stochastic inventory systems. This simple inventory decision model is reflective of many real life situations and is frequently used to assist human decision-making in fashion manufacturing and retail industry (Gallego and Moon, 1993) as well as service industry such as hotels and airlines (Pfeifer and Weatherford, 1994). For example, a fashion manufacturer will have to decide on its raw material and human resource requirements before the launch of a new product which becomes obsolete very quickly.

The economic impact of newsvendor decision-making is enormous. The US Bureau of Economic Analysis (www.bea.gov) has reported that the non durable good industry accounted for $2 trillion and the service industry accounted for more than $4 trillion of US annual gross domestic product in 2002. Food and apparel industries, most frequently modeled by SPP, accounted for more than $1.4 trillion of US GDP in 2002. Healthy life styles have increased the demand for fresh produce, which accounted for 9% of the $900 billion food industry in 2002. Any slight improvement to the decision-making in these newsvendor type business settings will undoubtedly increase profitability. For example, a fashion industry firm realized a 60% increase in profit when it implemented an algorithm to assist firm's managers with newsvendor decision-making (Fisher et al., 1996).

As product life cycles become shorter, more extensions to the classic SPP model are being considered (Moutaz, 1999 and Silver et al., 1998) such as how different risk preferences influence the decision-maker's order quantity. Agrawal and Seshadri (2000), for example show that a risk-averse newsvendor orders less than the optimal quantity of the risk neutral solution.

Empirical results of NV decision-making have discovered the subject's decision to systematically deviate from the well known theoretical SPP optimal solution. This human decision bias was first reported in a well conditioned experimental-based research on SPP in which subjects with prior classroom knowledge of SPP ordered too few of the high profit items and ordered too much of the low profit items (Schweitzer and Cachon, 2000). Bolton and Katok (2004) proposed different learning-by-doing environments to enhance the newsvendor performance by providing feedbacks to the subjects during the experiments. Though none of the 3 methods proposed completely eliminated human decision bias, a 10-period standing order strategy was identified to be most promising in improving newsvendor decision-making. Given the significance of SPP model, this persistent bias from its optimal solution definitely warrants a more thorough investigation.

This research contributes to the literature of SPP by providing the much needed laboratory evidence to validate various theoretical results of SPP. This empirical research of the SPP is important because:

(1) Without some empirical work, the practicality of newsvendor models cannot be assessed (Anwari, 1987). However, no laboratory evidence of SPP was found prior to 2000;

(2) Empirical data contradicts optimal solutions proposed by SPP models. The first empirical work on the SPP revealed a consistent deviation of newsvendor decision from the optimal solutions predicted by various utility models of SPP (Schweitzer and Cachon, 2000);

(3) Human decision bias is a reality and could not be eliminated by learning enhancement. The second and the latest empirical work on SPP revealed that the newsvendor decision bias remained in spite of enhancement to the learning environment by providing newsvendor subjects with improved decision support system (DSS) and reduction of potential decision error (reduced from 299/300 to 2/3) (Bolton and Katok, 2004);

(4) Many factors theoretically shown to affect newsvendor decision-making have not been empirically tested. Thus far, empirical studies of newsvendor decision-making have mainly focused on item profit margin as the main factor influencing human decision-making. For example, the significance of newsvendor's initial wealth, theoretically determined to be positively correlated to newsvendor order quantity (Eeckhoudt et al, 1995) has not been empirically tested;

(5) Potential problems of human decision bias found in systems of newsvendor type products have not been assessed. Stochastic optimization models used in the supply chain design problem often assume retailers order as consumer demand distribution predicts. Any human decision bias exhibited by the retailers of newsvendor type products might cause the model solution to be theoretically sub-optimal. Understanding and modeling human decision bias in the non-durable product systems might provide significant economic benefit due to the size of these industries.

This research will extend the current research of the SPP by specifically answering questions such as:

1. Does a newsvendor with higher initial wealth order more than a newsvendor with lower initial wealth?
2. Is there evidence that higher salvage value increases the bias towards more order quantity?
3. Does classroom learning of SPP improve newsvendor decision-making?
4. Does relationship between newsvendors affect the system performance?
5. How does human decision bias affect the design of NV systems?

In order to answer these important questions, we first set up a newsvendor decision-making model as a framework of our study of newsvendor's reliance on various NV requisition policies. These NV requisition policies are alternative to the classic NV requisition policy. Then, factorial experiments are conducted in single newsvendor and multi-echelons newsvendor settings to assess how different factors such as item profit margin, NV's initial wealth, item salvage value, and NV training affect newsvendor decision-making. Regression analysis and hypothesis testing methods are utilized to analyze a human decision bias model of different newsvendor ordering heuristics. Finally, we present case studies illustrating the implications of human decision bias on the performance of systems involving newsvendor type products.

The rest of this dissertation is arranged in the following order. Relevant literature reviews and extensions of SPP are presented in Chapter 2. Qualitative sensitivity analysis of how different initial wealth levels affect decision-maker's order quantity is presented in Chapter 3. A human decision bias model of various newsvendor requisition policies is discussed in Chapter 4. Single and multi-echelon newsvendor experiment analyses are presented in Chapter 5 and 6 respectively. A thorough discussion of the impact of human decision bias on the performance supply chain design and a case study of the US fresh produce industry are presented in Chapter 7. Chapter 8 summarizes some key empirical results of human decision bias in single and multi-echelon newsvendor settings and discusses the implication of our research to other Operation Research fields as well as possible extensions to this research.

CHAPTER 2: LITERATURE REVIEW

In this Chapter, we discuss previous research in the newsvendor model with risk followed by work in human decision bias.

2.1 Newsvendor Problem and Extensions

The literature of the newsvendor (NV) problem, the archetype of stochastic inventory research, is vast and its complete coverage is beyond the scope of any single chapter. Khouja (1999) provides a systematic categorization of various extensions to the classic single period problem (SPP). Some of the categories proposed such as: i) different objectives and utility functions, ii) multiple periods, and iii) multi-echelon systems are closely related to our research.

Consider a newsvendor who has only one opportunity in the morning to decide how many newspapers to order to satisfy the day's demand, *D*. Let *f* be the probability distribution function of the day's demand and let *F* be its cumulative probability distribution. If he orders too much, his cost will be too high. If he orders too little, he will miss out on additional profit. If the overage cost, c_o (item cost, *c* – salvage value, *s*) and the shortage cost, c_s (item price, *p* – item cost, *c*) are equals, it makes sense for the newsvendor to place an order quantity, *q* in such a way that the probability of demand less than *q, F(q)* equals the probability of actual demand exceeding *q, 1-F(q)*. Therefore, the newsvendor should order an amount of newspaper equivalent to average demand, $\overline{D}$. However, when the overage cost and the shortage cost are not equals, how then should the newsvendor order? If c_o is greater than c_s, then it makes sense to order less than $\overline{D}$, because the profit from an extra item sold is not worth as much as the cost of an extra item not sold. If c_o is less than c_s, then it makes sense to order more than $\overline{D}$, because the profit from an extra item sold is worth more than the cost of an extra item not sold. Therefore, the optimal order quantity, q^* that balances the expected overage cost and the expected shortage cost would need to satisfy:

$$c_o F(q^*) = c_s(1 - F(q^*))$$

or

$$F(q^*) = \frac{c_s}{c_o + c_s} \tag{1}$$

The SPP literature often refers to $\frac{c_s}{c_o + c_s}$ as the *critical fractile* of SPP. The rest of this dissertation defines critical fractile > 0.5 as high profit margin and critical fractile < 0.5 as low profit margin.

An important extension to the SPP for our work is incorporating risk preferences of the decision-maker. Lau (1980) considers the newsvendor problem under a new objective of maximizing expected utility in the form of E[Q] - λVar[Q], where Q is the return of investment and λ is the measure of risk aversion of the decision-maker. The analysis on the optimal solutions to SPP with different values of λ determines that an increase in risk-aversion negatively affects order quantity. Eeckhoudt, et al. (1995) examined the comparative static effects of different price and cost parameters in a risk-averse SPP framework. The risk-averse newsvendor was shown to order less as risk increases.

Another extension of SPP is the case where the newsvendor can adjust the selling price of the item. Agrawal and Seshadri (2000) showed the impact of uncertainty and risk aversion on the price and order quantity in the newsvendor problem. Demand was assumed to be a function of selling price. Investigators further defined a *scale* effect as a scaling of both the mean and the variance of the demand distribution and a *location* effect as the shifting of the mean of demand distribution without affecting the variance. If price affected the scale of the demand distribution, the risk averse newsvendor was found to order less and set higher price. If price affected the location of the demand, the risk-averse newsvendor was found to set lower price. Order quantity of the risk-averse newsvendor could not be determined because while lower price generates higher demand, an increase in risk-aversion will result in reduction of order quantity.

A newsvendor with multiple investment options is concerned about the covariance of risks of these investment options. Anvari (1987) modeled this single period newsvendor problem using a well known capital asset pricing model (CAPM), first independently proposed by Sharpe (1964) and Lintner (1965). Contrary to other working-capital decisions such as those proposed by Lau (1980), which might imply divergence of shareholders' and managers' objectives, the use of CAPM to analyze inventory problems need not imply conflicting assumptions. The resulting optimal policy is characterized and compared with the classical expected benefit maximization framework. It is shown that when the relevant risk of inventory investment is considered, the optimal order quantity can be dramatically lower than that of classic SPP model. Chung (1990) later tightens the optimality conditions and provides a simple solution method for normally distributed demand.

Inderfurth and Schefer (1996) extend SPP to a multi-period framework and present a periodic order-up-to-*S* policy. Optimality conditions for the reorder level *S* are derived for both the back-order and the lost-sales case. They analyze the effects of cost and price parameters, capital market data, and demand risk, in terms of correlation between demand and market return, on the reorder level. They find that as correlation between demand and market return increases, so does the risk in demand. Higher demand risk increases the opportunity cost of investment in inventory, and therefore, the reorder level of newsvendor product decreases.

2.2 Biases in Human Decision-Making

Limitations and biases in human decision-making have been well studied by psychologists and experimental economists. A particular human decision bias is the anchoring and adjustment effect. Human decision often arises from adjustment of a prior decision. Therefore, different starting values yield different estimates over time, which are biased towards initial values. Tversky and Kahneman (1974) demonstrated this effect by asking subjects to estimate the percentage of African countries in the United Nation. Subjects first observed a random number between 0 and 100, then asked if the random number was too high or too low of an estimate. Then the subjects were asked to provide a numerical estimate of the percentage of African states represented in United Nations. The results showed the random arbitrary number significantly affected the subjects' estimates, such as those who received 65 guessed 45% and those who received 10 guessed 25%.

Northcraft and Neale (1987) found that anchoring and adjustment bias was a limitation of decision-making in the business world with novice and expert decision-makers. Their results suggested that past experience and training did not have any impact on changing this human decision bias. Many computer based decision support systems (DSS) claimed to counter the anchoring and adjustment bias effect. Ahuja et al. (2000) tested a DSS designed to mitigate such anchoring and adjustment bias in a real estate pricing game and found that the anchoring and adjustment bias remained robust. The computer based DSS did not successfully mitigate or eliminate human decision bias because "the (human decision) bias that operates without the information system continues to operate within it."

2.3 Human Decision Bias in the Inventory Systems

Sterman (1989) stresses the need to incorporate the limitations and biases of human decision-making into management science and economics models:

> "Studies in the psychology of individual choice have identified numerous cognitive and other bounds on human rationality, often producing systematic errors and biases. Yet for the most part models of aggregate phenomena in management science and economics are not consistent with such micro-empirical knowledge of individual decision-making."

Some experimental economics studies have been conducted on supply chain systems of a single durable product to investigate human decision-making. Sterman (1989) modeled an inventory manager's behavior in a stock management game (the beer game). The decision model comprised of a desirable level of incoming inventory, a desirable level of current inventory, and a predicted level of outgoing inventory. Inventory managers were found to be biased towards the current inventory. Estimated parameters of the weigh subjects placed on current inventory had significantly higher value than those of incoming inventory. This human behavioral bias caused the amplification and oscillation of demand in the supply chain.

Schweitzer and Cachon (2000) confirmed that decision bias existed in the newsvendor problem. Groups of MBA students who had received training on the newsvendor problem within the last year were recruited as "expert" newsvendors. Each newsvendor had same initial wealth and was well informed of the characteristics of the demand. The experiments were conducted over both the high profit margin and the low profit margin conditions, *ceteris paribus*. The experiment was repeated 15 times and subjects were provided feedback after each round. Results from these studies demonstrated that decision-makers' choices systematically deviated from those that maximized expected profit. Subjects ordered too few of high-profit products and too many of low-profit products. Investigators conclude:

> "These results are not consistent with many objective formulations such as risk-aversion, risk-seeking preferences, prospect theory preferences, waste aversion, stock-out aversion, or the consequences of underestimating opportunity costs…A better understanding of actual behavior in real processes may lead to the discovery that traditional assumptions need modification, and that new techniques may be required to correctly optimize these systems."

Motivated by the human decision bias found in the newsvendor problem, Bolton and Katok (2004) investigated the effects of enhancement to the learning environment on the quality of newsvendor decision-making. Specifically, they set up three separate studies to investigate the effects of the extended experience and enhanced feedback on newsvendor decision-making. In the first study, a 100-period newsvendor game, investigators showed that as the game participants gathered more experience about the game, they tended to order closer to the optimum level. The second study focused on the effectiveness of various feedback enhancements such as information concerning the payoff of foregone options and a 10-period moving average of demand. Investigators found that none of these enhanced feedbacks had any significant effects on the quality of the newsvendor decision. In the last study, investigators tested the effectiveness of a standing order policy which restricted the game participants "to ordering a fixed quantity for a sequence of 10 periods". Under the standing order policy, the quality of newsvendor decision improved dramatically. This result suggested the potential benefits of limiting decision-maker's ability to react to short term trends. The practicality of such constraint in the real industry setting has not been addressed.

After reviewing theoretical analysis of various extensions to the newsvendor problem, another writer concludes, "Without some empirical work examining real life objectives of managers… the practicality of these (newsvendor) models cannot be assessed." (Anwari, 1987).

Current empirical studies, citing different newsvendor ordering heuristics as sources of human decision bias (Cachon and Schweitzer, 2000) lack a framework to test the newsvendor's preference on these heuristics. Therefore, a natural extension of the empirical research of SPP is a formulation of human decision bias model of multiple objectives to investigate newsvendor's reliance on these objectives. This model and its extension will be used throughout this dissertation as a comparative static framework to identify decision-makers' preferred ordering heuristics under different empirical study conditions.

Current empirical studies in SPP have mainly considered item profit margin as the main factor to influence newsvendor decision-making. Our work will extend the empirical studies of a single newsvendor decision-making to investigate the effects of initial wealth, item's salvage value, and *a priori* NV training on newsvendor decision-making. These factors have been proposed in the theoretical analysis of SPP to significantly affect newsvendor decision-making. Our work will provide the experimental evidence to validate if these factors are indeed significant.

Current empirical studies in SPP have only tested the newsvendor decision-making in a single newsvendor setting. Subjects in the single newsvendor setting faced computer generated demand. Our research will extend these empirical studies to a multi-echelon newsvendors setting where subjects will face both the computer generated and the human generated demand. These experiments will provide insights into the effect of supplier-retailer relationship on the performance of multi-echelon newsvendor systems.

CHAPTER 3: EFFECTS OF INITIAL WEALTH ON NEWSVENDOR DECISION-MAKING

In this Chapter we investigate the effect of initial wealth, w_0, on newsvendor decision-making under several alternative utility functions including risk-aversion, loss-aversion, bankruptcy-aversion, and a combination of loss and risk-aversion. Utility model analyses will reveal that NV's initial wealth can influence NV order quantity to deviate from the optimal order quantity.

3.1 Risk-Averse Newsvendor

In this section we investigate the effect of w_o on the optimal order quantity of a risk-averse newsvendor, q_a^*. We specifically answer the question: Does higher w_0 imply higher optimal order quantity for a risk-averse newsvendor? The answer to this question, as we will show, depends on the type of newsvendor's risk-aversion. We first present the notation used:

- w: The wealth of the newsvendor.
- w_0: The initial wealth of the newsvendor.
- $u(w)$: The newsvendor's utility function (we assume to be twice differentiable and monotonically increasing in w).
- $u'(w)$: The marginal utility of the newsvendor's wealth (We assume wealth to be desirable and hence $u'(w) > 0$).
- $u''(w)$: The rate of change of the marginal utility of newsvendor's wealth (By the definition of risk preference: (1) a risk-averse newsvendor has $u''(w) < 0$,

(2) a risk-neutral newsvendor has $u''(w) = 0$, and (3) a risk-seeking newsvendor has $u''(w) > 0$).

q^*: The optimal order quantity of a risk-neutral newsvendor with a utility maximizing objective (It is well known that the optimal order quantity of a risk-averse newsvendor, q_a^* is less than q^* and the optimal order quantity of a risk-seeking newsvendor, q_s^* is more than q^* (Eeckhoudt et al. 1995, and Schweitzer et al. 2000)).

$r_u(w)$: Arrow-Pratt Measures of Absolute Risk-Aversion (Pratt (1964) and Arrow (1965) introduced a measure of the strength of risk-aversion as $r_u(w) = -\frac{u''(w)}{u'(w)}$. By the definitions of u, $u'(w)$, and $u''(w)$, we see that $r_u(w)>0$ implies risk-aversion. The greater $r_u(w)$ is the more risk-averse a newsvendor is. Furthermore, $r_u(w)=0$ and $r_u(w)<0$ describe risk-neutral and risk-seeking respectively).

Three categories of absolute risk-aversion are described by the derivative of $r_u(w)$ as follows:

$r_u'(w) > 0$: Increasing Absolute Risk-Aversion (IARA) means the newsvendor is more risk-averse when she is wealthier. An example of IARA utility function is $u(w) = a + bw - cw^2$ where $c > 0$ and $w<b/2c$ which has $u'(w) = b - 2cw$ and $u''(w) = -2c$. Thus, $r_u(w) = 2c/(b - 2cw)$ and $r_u'(w) = \frac{4c^2}{(b-2cw)^2} > 0$. Notice that this quadratic utility function holds only for a limited range of $w < b/2c$, beyond which the additional wealth results in declining utility.

$r_u'(w) = 0$: Constant Absolute Risk-Aversion (CARA) means the newsvendor's risk-aversion does not change with her wealth. An example of a CARA utility function (Pratt, 1964) is $u(w) = -e^{-w}$ which has $u'(w) = e^{-w}$ and $u''(w) = -e^{-w}$. Thus, $r_u(w) = 1$ and $r_u'(w) = 0$.

$r_u'(w) < 0$: Decreasing Absolute Risk-Aversion (DARA) means the newsvendor is less risk-averse when she is wealthier. An example of a DARA utility function (Pratt, 1964) is $u(w) = w^{\alpha}$ where $\alpha : R \in (0,1)$. It has $u'(w) = \alpha w^{\alpha-1}$ and $u''(w) = \alpha(\alpha-1)w^{\alpha-2}$. Thus, $r_u(w) = \dfrac{1-\alpha}{w^{\alpha}}$ and $r_u'(w) = \dfrac{-\alpha(1-\alpha)}{w^{\alpha-1}} < 0$.

Baron (1973) shows that newsvendor's optimal order quantity decreases as her risk-aversion increases. The directions of the optimal order quantity change as a function of the initial wealth change are given in Table 1 for each of the risk categories.

Table 1: Optimal Order Quantities of Various Risk-Averse Newsvendors

	IARA	**CARA**	**DARA**
Increase in w_o	q_a^* decreases	q_a^* unchanged	q_a^* increases
Decrease in w_o	q_a^* increases	q_a^* unchanged	q_a^* decreases

3.2 Loss-Averse Newsvendor

In this section we investigate the effect of initial wealth, w_o, on the optimal order quantity of a loss-averse newsvendor, q_l^*. We specifically answer the question: Does higher w_o imply higher q_l^*?

Kahneman and Tversky (1979) first defined loss-aversion as follows: “An individual is loss-averse if she or he dislikes symmetric 50-50 bets and, moreover, the aversion to such bets increases with the absolute size of the stakes.” Consider the following utility function of a loss-averse decision maker:

$$u_l(w) = \begin{cases} u_n(w) & w \geq w_o \\ \lambda u_n(w) & w < w_o \end{cases} \tag{1}$$

where:

$u_n(w)$: The utility function of a risk-neutral newsvendor such as $u_n(w) = w$.

λ : The degree of loss-aversion ($\lambda > 1$).

It has been shown that the optimal order quantity of a loss-averse newsvendor, q_l^* is less than the risk-neutral benchmark, q^*. Further, q_l^* decreases as degree of loss-aversion increases (Cachon and Schweitzer, 2000). The graphical representation of the risk-averse utility function is shown in Figure 1.

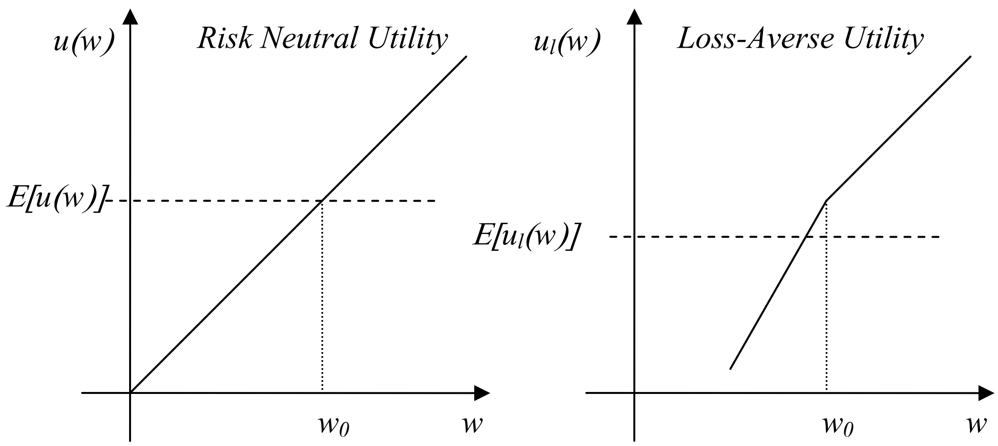

Figure 1: Comparison of Risk Neutral Utility and Loss-Averse Utility

In this Figure, the expected utility of a loss-averse decision maker is less than that of a risk-neutral decision maker. Therefore, the loss-averse newsvendor will avoid the risk of losing money by ordering less than a risk neutral newsvendor would. Simulation of the optimal order quantities for different values of λ reveals a downward trend of optimal order quantity for higher values of λ as shown in Figure 2.

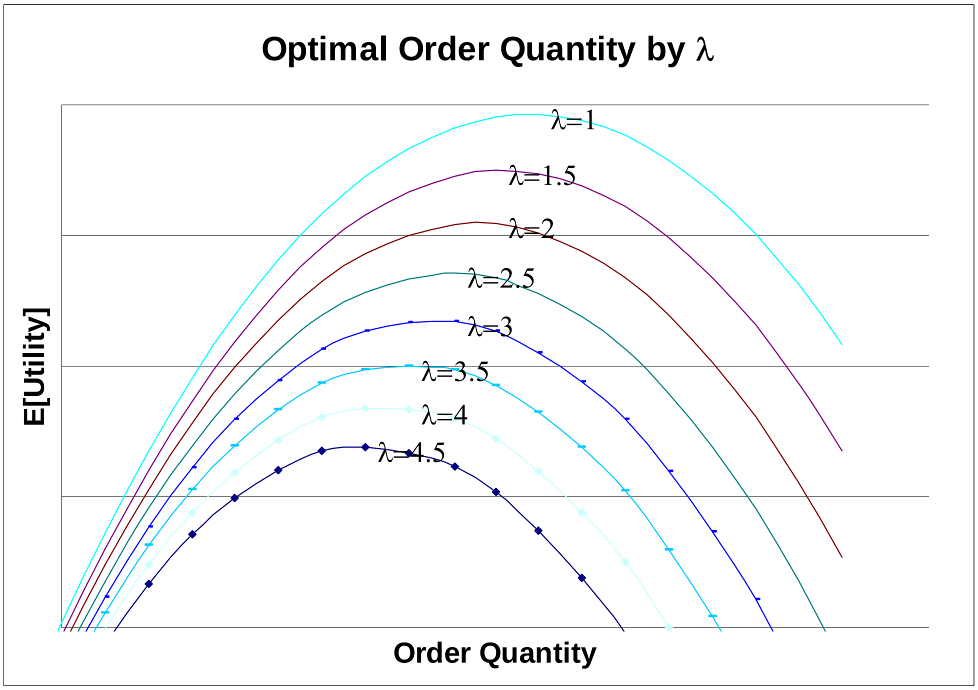

Figure 2: Expected Utility vs. Order Quantity under Various Penalty Values

However, notice that $u_l(w)$ is independent of w_o and therefore q_l^* is also independent of w_o. That is, the optimal order quantity of a loss-averse newsvendor with a constant degree of loss-aversion is independent of his initial wealth, w_o.

Next, we extend the loss-averse utility in (1) to include a maximum undesirable wealth level W_T is described by the following:

$$u_{lm} = \begin{cases} u_n(w_o + Q), & w_o + Q \geq w_o \\ \lambda_1 u_n(w_o + Q), & W_T \leq w_o + Q < w_o \\ \lambda_2 u_n(w_o + Q), & w_o + Q < W_T \end{cases} \tag{2}$$

where

w_o : The initial wealth.

Q : The profit function of order quantity and demand.

W_T : A maximum undesirable level of w and W_T=0 implies bankruptcy is undesirable.

λ_1, λ_2 : The degrees of loss-aversion ($\lambda_2 > \lambda_1 > 1$).

Graphical comparison between $u_{lm}(w)$ with $u_n(w)$ (Figure 3) shows that the aversion to loss increases when the wealth of the decision maker falls below a fixed threshold value, W_T. An example of a maximum undesirable wealth level is 0 which would imply that bankruptcy is undesirable. Notice also the condition $\lambda_2 > \lambda_1 > 1$ ensures a diminishing marginal rate of utility. The utility function $u_{lm}(w)$, which is a concave transformation of its risk neutral counterpart (Figure 3), has an optimal order quantity, q_{lm}^*, that is less than the risk-neutral benchmark, q^*.

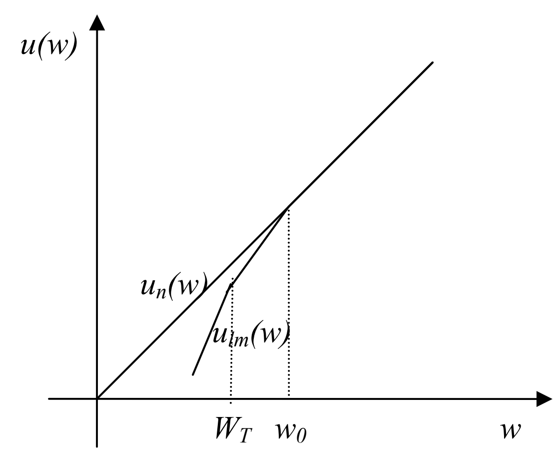

Figure 3: Graphs of Risk Neutral Utility and Loss-Averse Utility with Maximum Undesirable Wealth

The introduction of a W_T to the utility function changes the impact of w_o on the optimal newsvendor order quantity. We will show that the optimal order quantity of a wealthier newsvendor, q_{WRA}^*, is higher than that of a poorer newsvendor, q_{PRA}^*.

First, we define a wealthy newsvendor (WRA) as one whose maximum loss, Q_{min}, satisfies the conditions: $Q_{min} < 0$ *and* $w_o + Q_{min} \geq W_T$. A poor newsvendor (PRA) is defined as a newsvendor who is presented with a similar newsvendor investment opportunity as WRA, where the investment option has a maximum loss, Q_{min}, that satisfies the conditions: $Q_{min} < 0$ *and* $w_o + Q_{min} < W_T$.

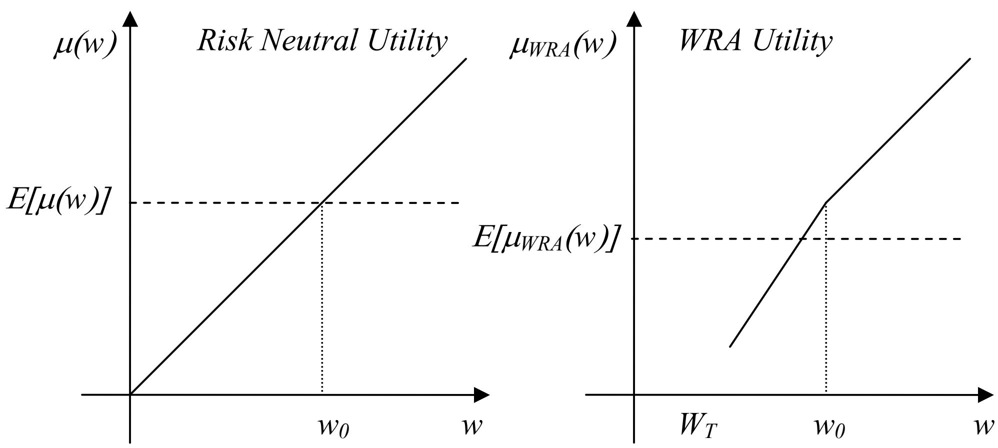

Figure 4: Graphs of the WRA Utility Function

Proposition 1: The optimal order quantity of a wealthy loss-averse decision maker (WRA), q_{WRA}^* is less than the optimal order quantity of a risk neutral decision maker, q_n^*.

Proof: From the definition of a wealthy newsvendor, $w_o + Q_{min} \geq W_T$, and therefore the utility function $u_{WRA}(w)$ is reduced to $u_l(w)$ as shown in Figure 4. Since $q_l^* < q_n^*$, it follows that $q_{WRA}^* < q_n^*$.□

Proposition 2: The optimal order quantity of a poor loss-averse decision maker (PRA), q_{PRA}^* is less than the optimal order quantity of WRA newsvendor, q_{WRA}^*.

Proof: We define P_A as probability that $Q \geq 0$, P_B as probability that $Q < 0$ and $w_o + Q \geq W_T$, P_C as probability that $Q < 0$ and $w_o + Q < W_T$. Notice that $P_A + P_B + P_C = 1$ and P_C

> 0. Since $\lambda_2 > \lambda_1$, so it follows that the expected utility of a PRA decision maker, $E[u_{PRA}]<E[u_{WRA}]$ as shown in Figure 5. This implies $q_{PRA}^* < q_{WRA}^*$.□

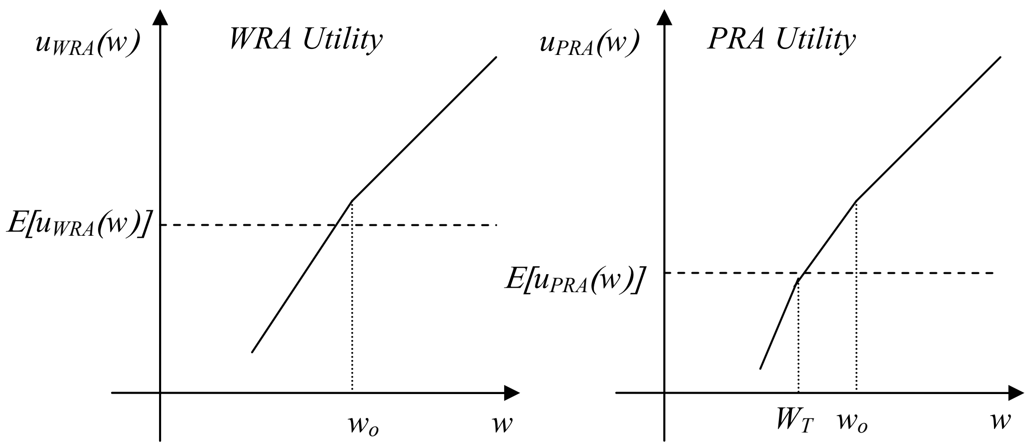

Figure 5: Graphs of the PRA Utility Function

The analysis of the utility of a loss-averse newsvendor reveals two different results as shown in Table 2. The initial wealth of a loss-averse newsvendor, w_o, affects newsvendor decision making when a fixed maximum undesirable wealth threshold exists, and the maximum loss (or a minimum profit), Q_{min}, incurred results in $w_o + Q_{min} < W_T$. Otherwise w_o has no impact on loss-averse newsvendor decision-making.

Table 2: Optimal Order Quantity of a Loss-Averse Newsvendor

	Loss-Aversion	**Loss-Aversion + W_T**
High w_o	q_l^* unchanged	$q_{lm}^* = q_l^*$
Low w_o	q_l^* unchanged	$q_{lm}^* < q_l^*$

3.3 Loss and Risk-Averse Newsvendor

In this section we discuss the effect of initial wealth, w_o, on the optimal order quantity of a loss and risk-averse newsvendor. This result extends from the current utility analysis of risk-aversion and loss-aversion. A generally risk-averse person can become fearful of losses when presented with an opportunity to invest in a risky investment. This loss-aversion effect can be described by a concave transformation of the person's utility function prior to becoming loss-averse. We purpose the use of concave transformation of the risk-averse utility function to create a loss and risk-averse utility function that is dependent on random variables w and w_o.

Consider the following utility function of a risk-averse decision maker who also fears loss.

$$u_{la}(w, w_o) = \begin{cases} u_a(w) & w \geq w_o \\ u_a(l(w_o)w) & w < w_o \end{cases} \tag{3}$$

where

$u_a(w)$: The risk-averse utility function.

$l(w_o)$: The loss-aversion function of w_o where $0< l(w_o) < 1$.

Loss aversion by definition is equivalent to a utility function that is steeper for losses than for gains (Kahneman and Tversky, 1979). A concave transformation of a risk-averse utility function by the proportion-of-wealth function, $l(w_o)$ creates the "steeper losses than for gains" property as shown in Figure 6. A discount function of wealth, 1- $l(w_o)$, in the case of loss satisfies the condition $u_a(w_o^1)= u_{la}(w_o^2, w_o^3)$ where $w_o^1 < w_o^2 < w_o^3$. This means that the utility of w_o^2 for a newsvendor given initial wealth of w_o^3 is equal to the utility of a newsvendor with initial wealth of w_o^1. Since $u_{la}(w)$ is a concave transformation of $u_l(w)$, the optimal order quantity of a loss and risk-averse newsvendor, q_{la}^* is less than that of a risk-averse newsvendor, q_a^*, since the expected utility function $u_{la}(w)$ is less than expected $u_a(w)$.

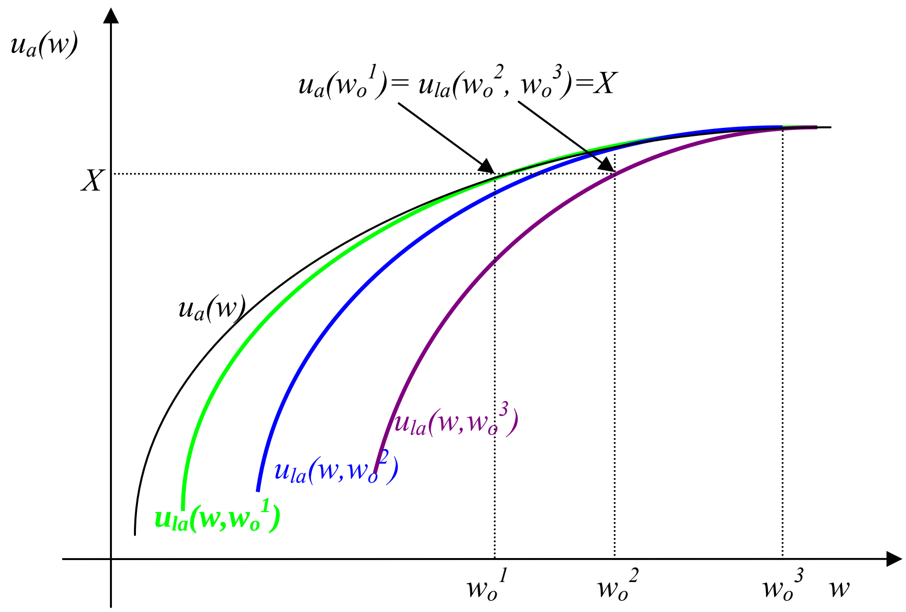

Figure 6: Loss and Risk-Averse Utility Function

Several properties of loss-aversions are described as follows:

$l'(w_o) <0$: Increasing Loss-Aversion (ILA) means the newsvendor is more loss-averse when she is wealthier. An example of ILA is $l(w_o)=1-\alpha w_o$ where $0<\alpha<1/w_o$. Notice that the wealth discount is increasing in w_o.

$l'(w_o) =0$: Constant Loss-Aversion (CLA) means the newsvendor's loss-aversion is independent of w_o. An example of CLA is $l(w_o)=\alpha$ where $0<\alpha<1$.

$l'(w_o) > 0$: Decreasing Loss-Aversion (DLA) means the newsvendor is less loss-averse when she is wealthier. An example of DLA is $l(w_o) = \alpha w_o$ where $0 < \alpha < 1/w_o$.

Next, we discuss the effect of w_o on the newsvendor's optimal order quantity under different combinations of absolute risk-aversion and loss-aversion. Recall our previous discussion of how w_o affects the optimal order quantity under various absolute risk aversions. Consider a DARA newsvendor who fears loss in a manner described by DLA. Given an increase in wealth, the DARA-DLA newsvendor's risk-aversion and loss-aversion will decrease, and hence the optimal order quantity will increase. By analogous arguments, we can summarize the effect of w_o on q_{la}^* as follows:

Table 3: Optimal Order Quantity of a Loss and Risk-Aversion Newsvendor

Increase in w_o	**IARA**	**CARA**	**DARA**
ILA	q_{la}^* decreases	q_{la}^* decreases	Indeterminate
CLA	q_{la}^* decreases	q_{la}^* unchanged	q_{la}^* increases
DLA	Indeterminate	q_{la}^* increases	q_{la}^* increases

The optimal order quantities for the cases of DARA-ILA and IARA-DLA are indeterminate due to conflicting interests of risk-aversion and loss-aversion. Consider the following DARA-ILA utility function:

$$u_{la}(w, w_o) = \begin{cases} w^{0.5} & w \geq w_o \\ \left(\dfrac{1}{2w_o + 1} w\right)^{0.5} & w < w_o \end{cases} \tag{4}$$

where $l(w_o) = \dfrac{1}{2w_o + 1}$.

Observe that $l'(w_o) < 0$ which implies an ILA. Graphically we see that as w_o increases the slope of utility function on the loss side increases (Figure 7). Notice the following property of ILA:

$$u_{la}(w,w_o^H) < u_{la}(w,w_o^L) \text{ for } w_o^H > w_o^L \text{ and } w < w_o^H$$

That is, the utility of a loss and risk-averse newsvendor with higher initial wealth is uniformly lower than the utility of a loss and risk-averse newsvendor with lower initial wealth after suffering a loss ($w<w_o$). An example is a person with an initial \$1000 that lost \$900 may be more discontent with the \$100 in hand, than another person with an initial \$200 that lost \$100. This would have caused the optimal order quantity to decrease as w_o increases. However, the decreasing absolute risk aversion for higher w_o retards the decision maker's inclination to decrease q_{la}^*.

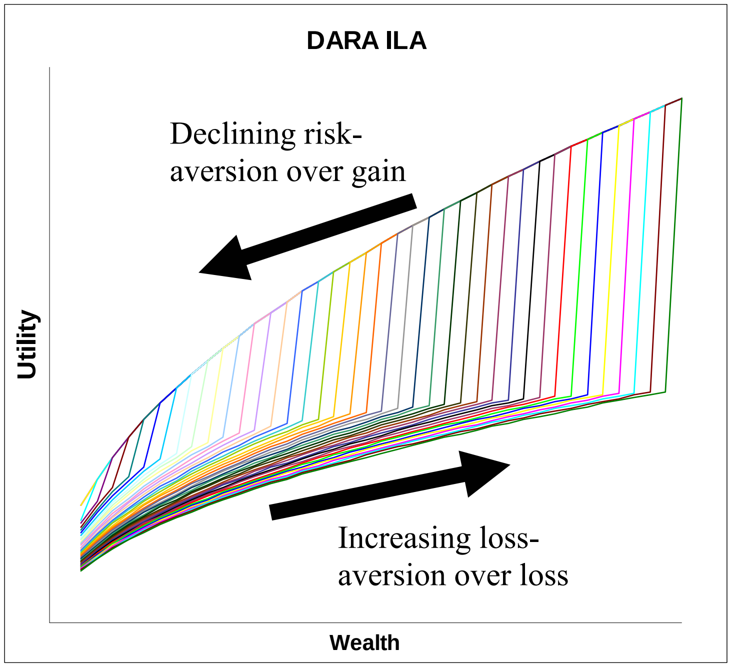

Figure 7: DARA-ILA Utility Function

Similar arguments could be made for the case of IARA-DLA newsvendor. Consider the following IARA-DLA utility function:

$$u_{la}(w, w_o) = \begin{cases} 4w - w^2 & w \geq w_o \\ 4(0.2w_o w) - (0.2w_o w)^2 & w < w_o \end{cases} \tag{5}$$

where $l(w_o) = 0.2w_o$ and $w<2$. Observe that $l'(w_o) > 0$, which implies a DLA. Graphically we see that as w_o increases the slope of utility function on the loss side increases (Figure 8). Notice the following property of DLA:

$$u_{la}(w,w_o^H) > u_{la}(w,w_o^L) \text{ for } w_o^H > w_o^L \text{ and } w < w_o^L.$$

That is, the utility of wealth is uniformly higher over loss for higher w_o. The DLA property generally would have caused the optimal order quantity to increase as w_o increases. However, the increasing absolute risk aversion for higher w_o retards the decision maker's inclination to increase q_{la}^*.

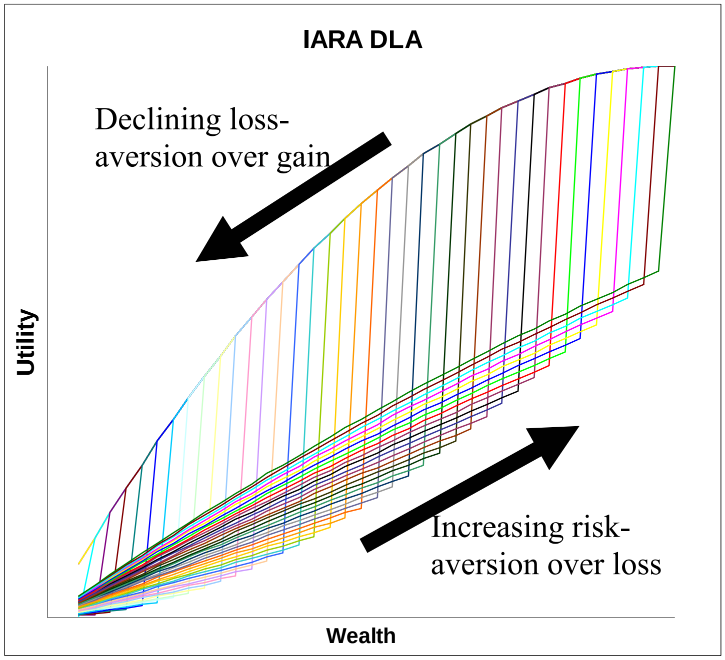

Figure 8: IARA-DLA Utility Function

The general characteristics of various loss-aversions are described by a side-by-side comparison shown in Figure 9. We utilized the constant absolute risk aversion (CARA) as the basis for this comparison. Notice that under DLA the $u_{la}(w,w_o^H)$ dominates $u_{la}(w,w_o^L)$ over the loss region and $u_{la}(w,w_o^L)$ dominates $u_{la}(w,w_o^H)$ under ILA. Under the CLA, the degree of loss-aversion is independent of w_o.

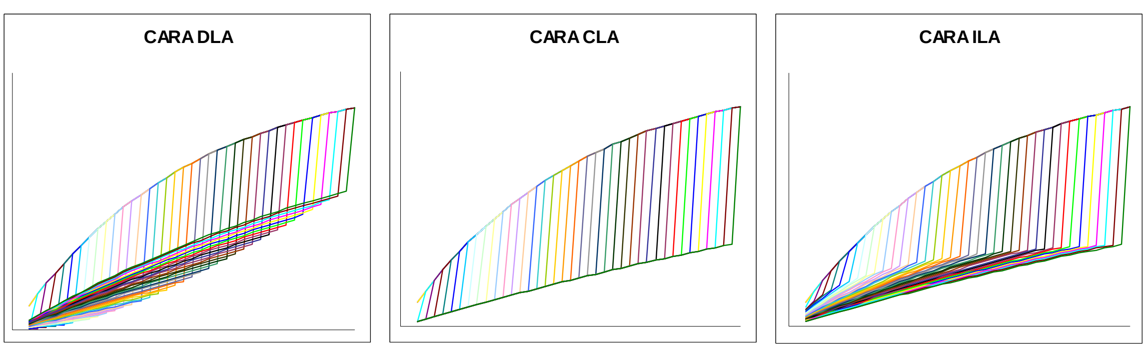

Figure 9: CARA Utility Functions for Various Loss-Aversions

In conclusion, different levels of initial wealth impact the newsvendor's optimal order quantities in different ways depending on her preference to risk and to loss. Empirical studies of newsvendor decision-making are presented in the following Chapters to highlight and discuss some of these seemingly contradictory results.

CHAPTER 4: MODELING HUMAN DECISION BIAS

In this Chapter we present various newsvendor requisition policies that result in human decision bias. We propose a multi-period newsvendor decision-making model of these newsvendor requisition policies to serve as a framework to investigate HDB. Hypotheses and implications of this human decision bias (HDB) model are discussed. Comparative static analyses of HDB further reveal interesting results consistent with existing newsvendor theories.

4.1 Formulation of Human Decision Bias Model

The purpose of the HDB model is to describe and to predict newsvendor decision-making that has been empirically proven to be inconsistent with any single utility theory such as risk-aversion, loss-aversion, and prospect theory (Schweitzer and Cachon, 2000). The investigators of NV decision bias conclude:

(1) "Subjects behave as if their utility function incorporates a preference to reduce ex-post inventory error, the absolute difference between the chosen quantity and realized demand."
(2) "Subjects suffer from the anchoring and insufficient adjustment bias."

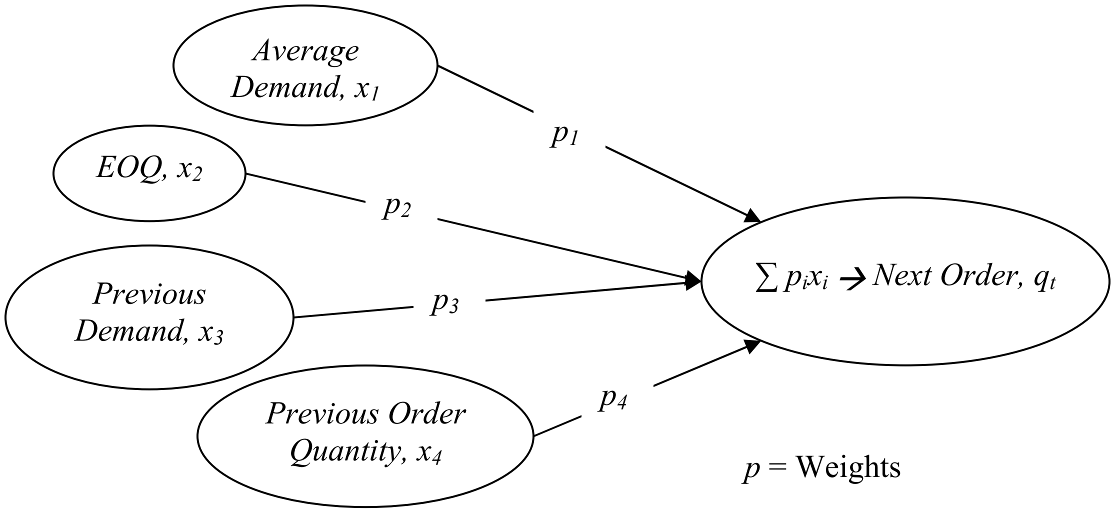

Figure 10: Newsvendor Decision Diagram

Four NV procurement policies are derived from these results. Conclusion (1) suggests that newsvendor decision-making to incorporate the procurement policy of ordering at the average demand level, which will minimize ex-post inventory error, into the classic NV profit maximizing solution. Conclusion (2) introduces the anchoring and adjustment heuristic, a decision process of anchoring at a reference point and then adjusting decision after receiving feedback from the system, similar to one used in a non-perishable inventory setting (Sterman, 1989). Some reasonable reference points for this procurement heuristic are decision-maker's previous order quantity and the average demand. Demand chasing heuristic, the preference to adjust towards the previous realization of demand, has also been proposed as a significant heuristic to explain newsvendor decision-making. Figure 10 illustrates the NV decision-making as a weighted sum of the following NV procurement heuristics:

1. The policy of ordering at the expected demand level, $\overline{D}$.

2. The policy of ordering at profit maximizing economic order quantity (EOQ) level, q^*. Assuming newsvendor is risk-neutral and so it follows that,

   $q^* = F^{-1}\left(\dfrac{p-c}{p-s}\right)$.

3. The policy of ordering at previous realization of demand level, D_{t-1}.
4. The policy of ordering the previous order quantity, q_{t-1}.

Formally expressed by the following multivariable linear equation:

$$q_t = p_e\overline{D} + p_u q^* + p_d D_{t-1} + p_q q_{t-1} \tag{1}$$

where:

q_t :	Order quantity at time t
p_e :	Weight of decision-maker's reliance on $\overline{D_t}$
p_u :	Weight of decision-maker's reliance on EOQ
p_d :	Weight of decision-maker's reliance on D_{t-1}
p_q :	Weight of decision-maker's reliance on q_{t-1}
$\overline{D}$:	Perceived expected value of demand
q^*:	EOQ of a risk neutral NV, $q^* = F^{-1}\left(\dfrac{p-c}{p-s}\right)$
D_t :	Realization of demand at time t.

Hypotheses testing of HDB model parameters, the weights decision-makers put on different procurement heuristics, will prove the significance and the direction of procurement heuristics' influence on newsvendor decision-making.

Hypothesis 5.1: Expected Demand Heuristic Hypothesis

$$H_0 : p_e \leq 0$$

$$H_1 : p_e > 0$$

Hypothesis 5.1 is that the expected demand ordering policy will influence the newsvendor decision-making. The expected demand policy is attractive to a decision-maker who wants to minimize the number of overages and shortages. Expected demand is often used in stochastic programming problems involving uncertainties in demand. We would reject H_0 if $t_0 > t_{\alpha,n-1}$ and conclude with 1-α confidence that the expected demand heuristics significantly affects newsvendor decision.

Hypothesis 5.2: EOQ Heuristic Hypothesis

$$H_0 : p_u \leq 0$$

$$H_1 : p_u > 0$$

Hypothesis 5.2 is that the policy of ordering the quantity defined by EOQ will influence NV decision-making. We would reject H_0 if $t_0 > t_{\alpha,n-1}$. If H_0 is rejected, then we would conclude with 1-α confidence that decision-makers rely on the utility model solution to determine their next order quantities.

The EOQ of the risk-neutral NV captures two influential factors on the NV optimal order quantity: the item profit margin and the demand distribution. Comparative static results of components of item profit margin such as the unit sale price, the unit cost, and the salvage value of the SPP are as follows: (1) if unit sale price goes up, *ceteris paribus*, the EOQ quantity will increase as well, and if unit sale price goes down, *ceteris paribus*, the EOQ quantity will decrease as well; (2) Higher unit cost of the newsvendor product leads to lower EOQ quantity and lower unit cost leads to higher EOQ quantity; (3) Higher salvage value generally leads to higher EOQ and lower salvage value leads to lower EOQ quantity.

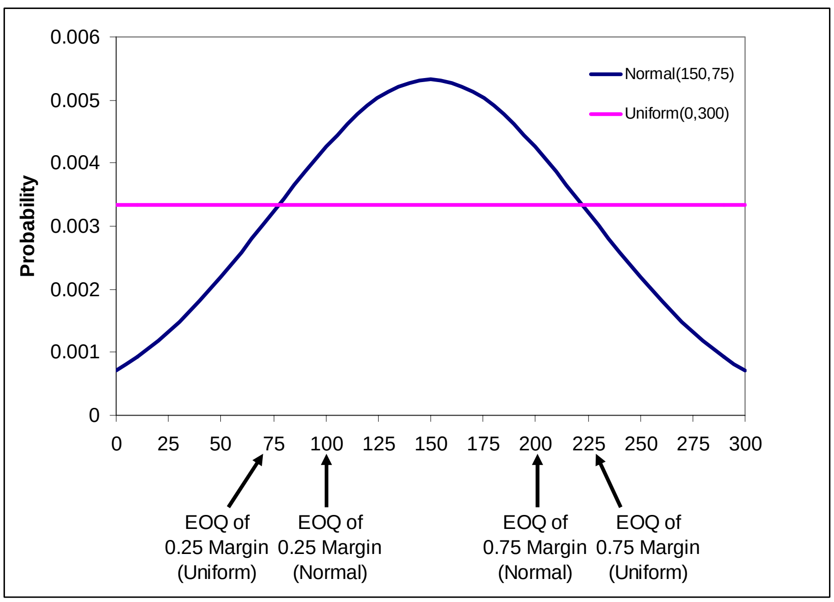

Figure 11: Comparison of the EOQs of Different Types of Demand Distributions

The changes in the mean, variance, and type of demand distribution affect the EOQ quantity differently. A higher mean leads to a higher EOQ quantity and a lower mean leads to lower EOQ quantity, *ceteris paribus*. A higher variance increases the EOQ quantity for high profit margin products and reduces the EOQ quantity of low profit margin products. Changes in the type of demand distribution also affect the EOQ quantity. Comparison of 2 distributions with identical mean and variance (Figure 11) shows the EOQ quantities of a high profit margin item is higher when demand is uniformly distributed. On the other hand, the EOQ quantity of a low profit margin item is lower when demand is uniformly distributed.

Hypothesis 5.3: Demand Chasing Hypothesis

$$H_0 : p_d \leq 0$$

$$H_1 : p_d > 0$$

Hypothesis 5.3 is that the demand chasing policy will influence the newsvendor decision-making. We reject H_0 if $t_0 > t_{\alpha,n-1}$ and conclude with 1-α confidence that newsvendor decision-making is influenced by demand chasing heuristic.

Hypothesis 5.4: Previous Order Preference Hypothesis

$$H_0 : p_q \leq 0$$

$$H_1 : p_q > 0$$

Hypothesis 5.4 is that the policy to order at the previous order quantity level will significantly influence NV decision-making. We reject H_0 if $t_0 > t_{\alpha,n-1}$ and conclude with 1-α confidence that newsvendor decision-making is influenced by the preference to anchor at the previous order quantity level.

Hypothesis 5.5: HDB model completeness hypothesis

$$H_0 : p_e + p_u + p_d + p_q = 1$$

$$H_1 : p_e + p_u + p_d + p_q \neq 1$$

Hypothesis 5.5 is that the HDB model is a weighted average of different newsvendor ordering policies. We reject H_0 if $t_0 > t_{\alpha,n-1}$ and conclude with 1-α confidence that newsvendor decision-making can be treated as weighted average of four different ordering policies.

Various empirical studies will be set up before and after a formal training session on SPP for newsvendor subjects to test these hypotheses in Chapter 5.

4.2 Comparative Static Analyses of HDB Model

This section discusses the significance of the decision-maker's initial order quantity and the comparative static analysis of the effect of sale price, *p*, unit cost, *c*, and salvage value, *s* on the HDB model.

Analysis of first order quantity

The newsvendor's first order quantity is important for two reasons. First, if the previous order quantity preference hypothesis is significant, then the first order quantity will be an important reference for the decision-maker's subsequent decisions. Second, many perishable items such as fashion goods and Christmas ornaments are seasonal, and the retailer may only be able to place one order for the whole selling season.

Let us expand the HDB model in terms of *t* as follows:

$$q_t = p_e\overline{D} + p_u q^* + p_d D_{t-1} + p_q(p_e\overline{D} + p_u q^* + p_d D_{t-2} + p_q(p_e\overline{D} + p_u q^* + p_d D_{t-3} + \cdots + p_q(p_e\overline{D} + p_u q^* + p_d D_1 + p_q q_1))) \tag{2}$$

Next, assuming that the demand distribution, D is i.i.d., we further simplify (2) as:

$$q_t = p_e[1 + p_q + p_q^2 + \cdots + p_q^{t-2}]\overline{D} + p_u[1 + p_q + p_q^2 + \cdots + p_q^{t-2}]q^* + p_d[1 + p_q + p_q^2 + \cdots + p_q^{t-2}]D + p_q^{t-1}q_1 \tag{3}$$

which can be rewritten as follows:

$$q_t = [1 + p_q + p_q^2 + \cdots + p_q^{t-2}](p_e\overline{D} + p_u q^* + p_d D) + p_q^{t-1}q_1 \tag{4}$$

Let $S_t = \sum_{n=0}^{t-2} p_q^n$ (5)

Multiplying both sides of (5) by p_q gives

$$p_q S_t = \sum_{n=1}^{t-1} p_q^n \tag{6}$$

Subtracting (6) from (5) then gives

$$(1 - p_q)S_t = 1 - p_q^{t-1}$$

$$S_t = \frac{1 - p_q^{t-1}}{1 - p_q} \tag{7}$$

Substituting (7) and (5) into (4) gives:

$$q_t = \frac{1 - p_q^{t-1}}{1 - p_q}(p_e\overline{D} + p_u q^* + p_d D) + p_q^{t-1}q_1 \tag{8}$$

Since we would not have a previous order quantity for $t = 1$, (8) will only apply when $t > 1$.

For the case of $0 \le p_q < 1$ and $t < \infty$, $\frac{dq_t}{dq_1} = p_q^{t-1}$, which is a decreasing function of t. This implies that the influence of the first order quantity, q_1 is greatest during the early periods of ordering. Graphical representation of the convergence rate of p_q^{t-1} (Figure 12) indicates that there are diminishing returns to the influence of the first order quantity for a small value of p_q, and that the influence of first order quantity remains high for large values of p_q.

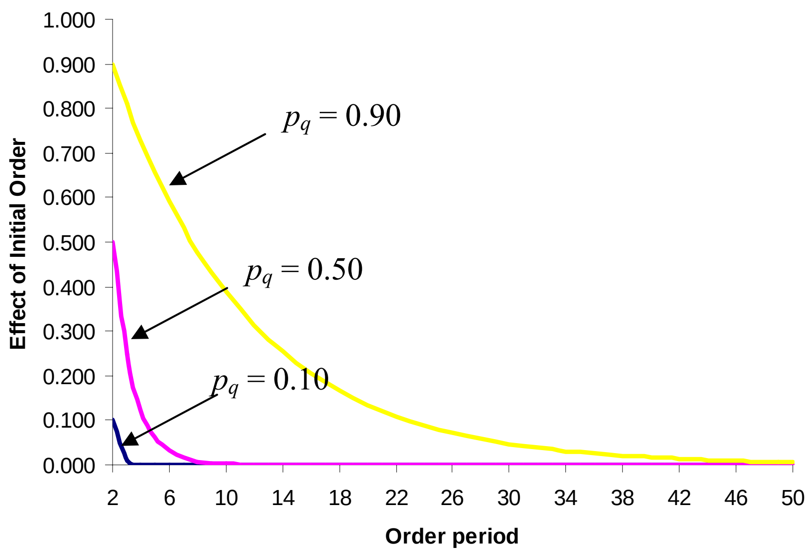

Figure 12: Effects of Initial Order Quantity

For $0 \le p_q < 1$ and $t \to \infty$, the sum of (5) converges to $\frac{1}{1-p_q}$, which simplifies (8) as:

$$q_t = \frac{1}{1-p_q}(p_e\overline{D} + p_u q^* + p_d D) \tag{9}$$

Since the term q_1 has disappeared, the HDB model suggests that in the long run the first order quantity, q_1 will not significantly affect the decision-maker's order quantity.

Comparative Static Analysis of the HDB

The section discusses the comparative static analysis of the effects of different NV cost parameters on the HDB. Specifically, we will investigate the impact of NV cost parameters in the long run HDB model under a uniform demand distribution assumption.

Assuming the demand is Uniform (*A, B*) where *A, B* > 0, then the optimal order quantity formula, $q^* = F^{-1}\left(\frac{p-c}{p-s}\right)$ yields

$$q^* = \frac{p-c}{p-s}(B-A)+A \tag{10}$$

Substituting (10) into (9) gives

$$q_t = \frac{1}{1-p_q}\left(p_e\overline{D} + p_u\left(\frac{p-c}{p-s}(B-A)+A\right)+p_d D\right) \tag{11}$$

Taking the derivative of (11), $\frac{dq_t}{dp} = \frac{p_u(B-A)}{1-p_q}\left[\frac{d}{dp}\left(\frac{p-c}{p-s}\right)\right]$ and applying the quotient rule we get $\frac{dq_t}{dp} = \frac{p_u(B-A)}{1-p_q}\left[\frac{-s+c}{(p-s)^2}\right]$.

Since $p>s$, then $(p-s)^2>0$. The salvage value, *s* is assumed less than unit cost, *c*, and therefore, $-s+c>0$. Lastly, $\frac{p_u(B-A)}{1-p_q}>0$, and so we conclude that $\frac{dq_t}{dp}>0$, which implies that the unit price, *p* is positively correlated with the order quantity, q_t.

The first order condition for q_t with respect to unit cost c is

$$\frac{dq_t}{dc} = \frac{p_u(B-A)}{1-p_q}\left[\frac{d}{dc}\left(\frac{p-c}{p-s}\right)\right] = \frac{p_u(B-A)}{1-p_q}\left(\frac{-1}{p-s}\right)$$

Since $\frac{p_u(B-A)}{1-p_q} > 0$, then $\frac{dq_t}{dc} < 0$, which implies that the unit cost, c negatively influences the order quantity, q_t. Intuitively, when the cost of an item increases, *ceteris paribus*, the newsvendor's order quantity will decrease.

The first order condition of q_t with respect to the salvage value is

$\frac{dq_t}{ds} = \frac{p_u(B-A)}{1-p_q}\left[\frac{d}{ds}\left(\frac{p-c}{p-s}\right)\right]$ and applying the quotient rule we will get

$\frac{dq_t}{ds} = \frac{p_u(B-A)}{1-p_q}\left[\frac{p-c}{(p-s)^2}\right]$. Since $p>s$, then $(p-s)^2>0$. The unit price, $p > c$, and $\frac{p_u(B-A)}{1-p_q} > 0$. We therefore conclude that $\frac{dq_t}{ds} > 0$, which implies that unit salvage value, s positively influences the order quantity, q_t. Intuitively, when the salvage value of an item increases, the profit margin of the item also increases, *ceteris paribus*, the newsvendor's order quantity will also increase.

4.3 HDB Parameters Estimation Approach

This section discusses the multivariable linear regression technique to estimate the significance of the HDB model parameters.

We select the traditional frequentist parameter estimation approach instead of the more subjective Bayesian (Hines and Montgomery, 1990) approach for following reasons. (1) We would not to able to specify a satisfactory a *priori* distribution due to the fact that we didn't have any prior information on the probability distribution for different ordering policies; (2) The factorial experimental designs we planned to check the significance of factors such as wealth, salvage value, and relationship between supplier and retailers rely on the frequentist approach. The effect estimates of the 2^k design are least squares estimates (LSD) (Montgomery, p. 549, 1997); and (3) Reasonably good estimates of the parameters of the HDB model with the LSE method can be obtained for a sufficient number of runs and subjects.

The HDB model parameters need to be transformed into the following multivariable linear regression model:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots + \varepsilon \qquad (12)$$

This transformation is proposed because it is more difficult to evaluate the quality of the fitted HDB model in its present condition, a linear regression model with zero intercept. Myers (1990) shows that the coefficient of determination, R^2, which is a measure of the fit of the regression line, may be inflated because the total sum of squares is not corrected for the mean for the zero intercept case.

The HDB parameters can be expressed in a more general multivariate linear regression model (12) without the loss of generality. First, the dependent variable Y can conveniently be replaced by q_t. Second, the intercept estimate, β_0 can be replaced by $p_e \overline{D}$. The HDB model assumes zero intercept and i.i.d. demand distribution, so we can treat the expected demand term, $p_e \overline{D}$ as the intercept term for the general multivariate linear regression model. Third, the slopes and predictors variables $\beta_1 x_1$, $\beta_2 x_2$, and $\beta_3 x_3$ are replaced by $p_u\, q^*$, $p_d\, q_D$, and $p_q\, q_{t-1}$.

CHAPTER 5: SINGLE NEWSVENDOR EXPERIMENTS

This Chapter presents the empirical results of two single newsvendor decision-making experiments. These experiments are set up to test the hypotheses from previous two chapters. The response variable for all experiments is the newsvendor's order quantity. The independent variables for the first experiments are the newsvendor's initial wealth and item profit margin. The independent variables for the second experiments are item profit margin and item salvage value.

5.1 Experiment I: Effects of NV Initial Wealth and Item Profit Margin

This section presents empirical results of statistical analysis of the effects of newsvendor's initial wealth and item profit margin on newsvendor (NV) decision-making. This empirical study extends current empirical studies of the NV problem which have only tested the significance of item profit margin (Schweitzer and Cachon, 2000, Bolton and Katok, 2004). Undergraduate student subjects from the School of Industrial and Systems Engineering at Georgia Tech were recruited to participate in this experiment. These students were enrolled in a required undergraduate course that would teach the concept and the formulation of the classical newsvendor problem. This group of students participated in this experiment before and after they learned the concept and formula of the NV problem.

5.1.1 Experiment I Design and Protocols

This 2^2 factorial design experiment has four treatment levels (Table 4). The NV's initial wealth factor has two levels. Subjects under the low initial wealth (W-) condition are informed to imagine they have \$500 to invest and subjects under the high initial wealth (W+) condition are informed they have \$10000 to invest. The item profit margin, defined as $\frac{p-c}{p-s}$ has two levels. The low profit margin (0.25) or high cost condition (C+) has a cost structure of p=\$12, c = \$9, and s = \$0. The high profit margin (0.75) or low cost condition (C-) has cost structure of p=\$12, c = \$3, and s = \$0.

Table 4: Newsvendor Experiment I Treatment Levels Summary

Treatment 1 (C-W+)	Treatment 2 (C+W+)	Treatment 3 (C+W-)	Treatment 4 (C-W-)
Wealth: \$10000 Revenue: \$12 Cost: \$3 Salvage: \$0	Wealth: \$10000 Revenue: \$12 Cost: \$9 Salvage: \$0	Wealth: \$500 Revenue: \$12 Cost: \$9 Salvage: \$0	Wealth: \$500 Revenue: \$12 Cost: \$3 Salvage: \$0

Each treatment level is replicated ten times. The subjects are instructed to order in such a way that would maximize their final wealth. The subjects are not informed of the length of the experiment and were told that it could end at any time. The actual demand is randomly generated during the experiment.

Detailed procedure:

1. Each subject is provided with the consent form to participate in the experiment voluntarily and is informed that the subject can quit anytime during the experiment without penalty.

2. Upon receipt of consent form, the principal investigator will provide each subject with the past demand data.
3. Subject is informed of the current wealth level and the current cost structure of the item.
4. Subject is asked to place an order within the demand range.
5. Subject places the order quantity.
6. Subject receives information about the actual demand for that period and its resulting profit or loss.
7. Subject reviews the demand data and current wealth.
8. Subject repeats step 3 for 40 order periods (10 runs for each treatment).

Of 26 subjects who participated in the experiment, only 24 subjects completed the experiments. All subjects underwent the same procedure with the same set of demand data. The experiment, conducted in May, 2004, was certified by the Georgia Institute of Technology Institute Review Board (IRB).

5.1.2 Experiment I Results and Analysis (Before Learning NV)

This section presents the statistical analyses of the data collected from this experiment in five major categories:

1. Factorial design experiment analyses.
2. Analyses of mean and variance of NV order quantity.
3. Analyses of NV order quantity adjustments over time and wealth.
4. Analyses of NV performance in term of profits, shortages, and overages.
5. Hypotheses testing of the HDB model.

5.1.2.1 Factorial design experiment analyses

This factorial experiment analysis investigates the significance of the NV's initial wealth term and the item profit margin term on newsvendor order quantities before subjects receive formal training on NV problem. The average order quantity of all subjects from each treatment level replication is compiled in such a way that each treatment condition has 10 data points. Figure 13 presents the normal probability plot of residuals. Other than some slight tail effects, the data appears normal.

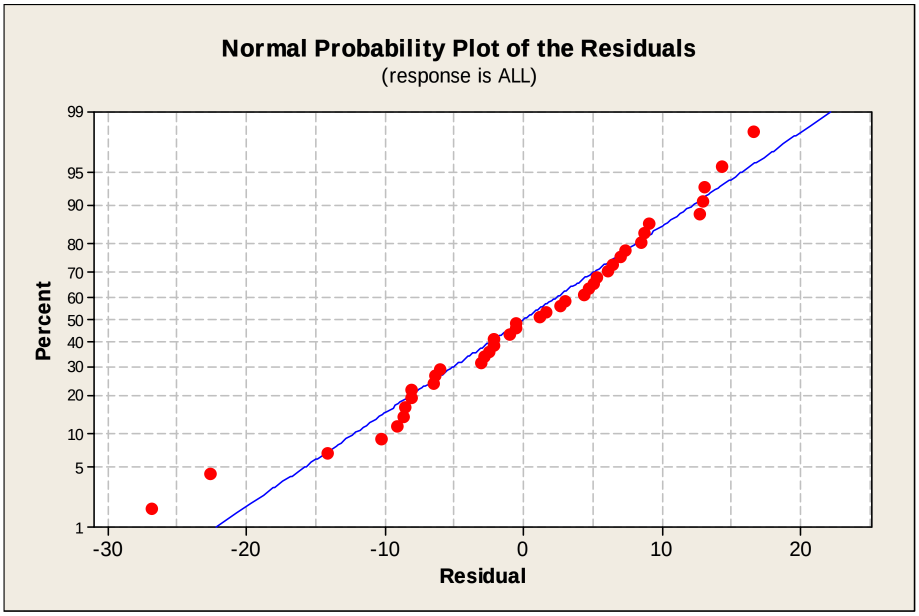

Figure 13: Exp. I (Before Learning NV) Normal Probability Plot of the Residuals

Average order quantity

This factorial design experiment is set up and analyzed in the MINITAB version 14 software. Figure 14 displays the effect estimates, the regression coefficients, and the sum of squares for each main effect and interaction terms. For these subjects, this statistical analysis indicates the subject's initial wealth, the item profit margin, and the interaction between these two factors to significantly affect human-determined newsvendor order quantity. The estimated effects for the aggregate data set shows the initial wealth term had positive effect of 10.43 which means higher order quantity is selected by subjects at the high initial wealth level. The estimated effects for the cost term is -56.28 which means the subjects in this experiment order less when the item cost is higher.

Estimated Effects and Coefficients for ALL (coded units)

Term	Effect	Coef	SE Coef	T	P
Constant		129.92	1.571	82.68	0.000
Wealth	10.43	5.22	1.571	3.32	0.002
Cost	-56.28	-28.14	1.571	-17.91	0.000
Wealth*Cost	15.68	7.84	1.571	4.99	0.000

Analysis of Variance for ALL (coded units)

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Main Effects	2	32762.0	32762.0	16381.0	165.86	0.000
2-Way Interactions	1	2458.4	2458.4	2458.4	24.89	0.000
Residual Error	36	3555.5	3555.5	98.8		
Pure Error	36	3555.5	3555.5	98.8		
Total	39	38775.9				

Figure 14: Exp. I (Before Learning NV) Factorial Design Analysis and ANOVA Summary

For these data, the cost and initial wealth interaction plot (Figure 15) shows that initial wealth effect is very small when the cost is low (C-) and very large when the cost is high (C+). This interaction plot also shows that the cost effect is large when initial wealth is low or high. Therefore, we can conclude that initial wealth effect affects the subjects' NV decisions most when item cost is high and that the item profit margin effect affects the subjects' NV decisions regardless of the levels of newsvendor's initial wealth.

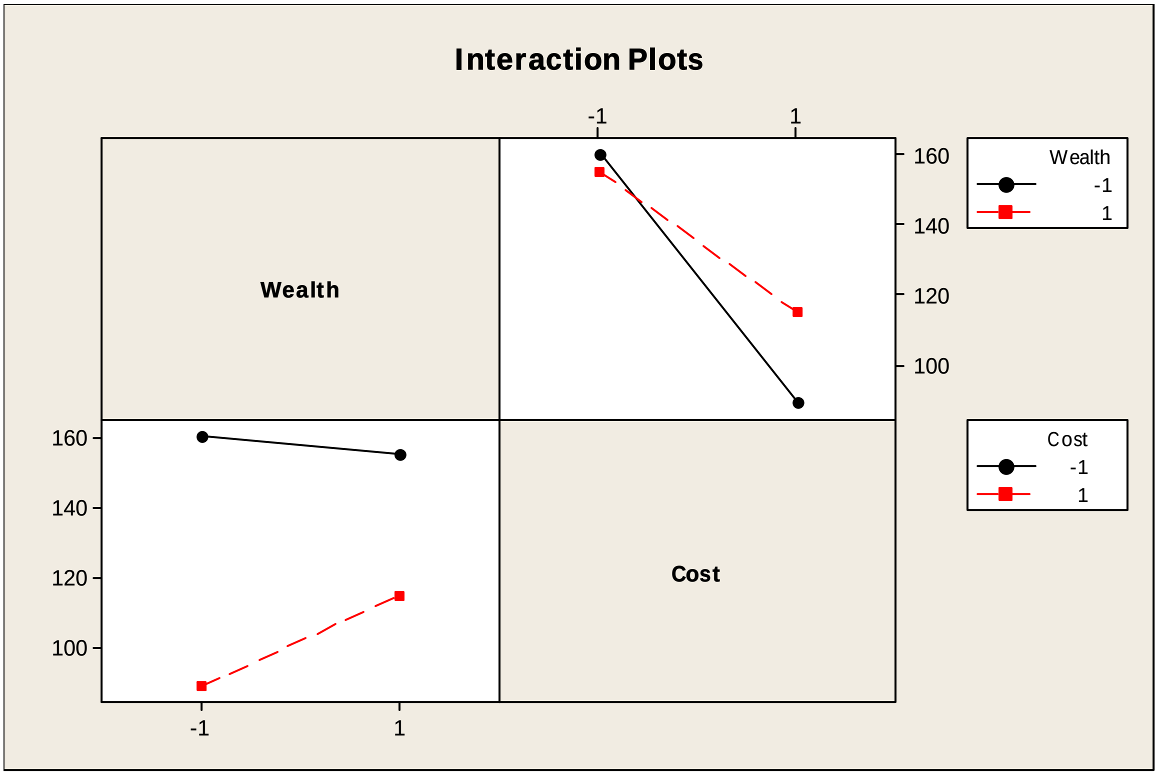

Figure 15: Exp. I (Before Learning NV) Interaction Plots

Individual order quantity

This section investigates the percentage of NV subjects whose decision-making is influenced by either the item cost term or the initial wealth term. The analysis results (Table 5) show that 87.5% of the subjects were influenced by at least one of the main factors. The item profit margin and the initial wealth factors affected the decisions of 83.3% and 37.5% of the subjects respectively.

Table 5: Exp. I (Before Learning NV) Summary of Percentage of Participants with Significant Factors

Factor	Significant	Not Significant
Cost	83.3%	16.7%
Wealth	37.5%	62.5%
Either one	87.5%	12.5%

5.1.2.2 Descriptive statistics of NV order quantity

The analysis of decision-maker's first order quantity enables us to make a comparison of treatment effects that is not confounded by the potential effects of experience and feedback. For these subjects, the statistical results (Table 6) indicate that the first inventory orders by subjects who faced the low cost conditions was significantly higher than the high cost conditions ($t(23) = 5.17$, $p<0.001$). On average, the first inventory order of subjects who faced the high wealth conditions was significantly higher than those subjects with the low wealth conditions ($t(23) = 4.38$, $p<0.001$). On average, the first inventory orders of subjects who faced high cost condition were above the mathematically optimal expected profit maximizing order quantity of 75 ($t(23) = 3.22$, $p<0.005$). On average, the first inventory orders of subjects who faced low cost condition were below the mathematically expected profit maximizing order quantity of 225 ($t(23) = 9.19$, $p<0.001$). On average, the first inventory orders were below the expected demand of 150 under all conditions, but this difference was only significant for the high cost conditions ($t(23) = 10.41$, $p<0.001$) and was not significant for the low cost conditions ($t(23) = 0.87$, p = n.s.).

Table 6: Exp. I (Before Learning NV) Statistics of Initial Order Quantity

Treatment	Average	Standard Deviation
C-W+	146.33	45.65
C+W+	123.54	36.76
C+W-	61.88	30.49
C-W-	138.04	59.63

The results of the one sample *t*-test comparisons of the subject's average order quantity and the expected demand (150) confirmed that order quantities of the subjects in treatment conditions C-W- (t(239)=3.09, p-value < 0.005), C+W- (t(239)=-29.36 p-value <0.001), and C+W+ (t(239)=-11.19 p-value < 0.001) significantly deviated from the expected demand. The order quantities under high cost (C+) conditions deviated most significantly from the expected demand (150). The average order quantity in the high cost and low wealth (C+W-) condition was 41% less than the expected demand.

The one sample t-test results indicate the subject's order quantities under all four treatment conditions to exhibit significant deviation from their respective mathematically optimal profit maximizing EOQs. On average, the average inventory orders of subjects who faced high cost conditions were above the expected profit maximizing EOQ of 75 (t(479)= 13.55, p-value <0.0001). On average, the average inventory orders of subjects who faced low cost conditions were below the expected profit maximizing EOQ of 225 (t(479)= -28.04, p-value <0.0001).

Variable	N	Mean	StDev	SE Mean
C-W+	240	155.44	51.08	3.30
C+W+	240	114.84	48.66	3.14
C+W-	240	88.73	32.33	2.09
C-W-	240	160.68	53.49	3.45

Variable	95.0% CI
C-W+	(148.94, 161.93)
C+W+	(108.65, 121.03)
C+W-	(84.61, 92.84)
C-W-	(153.88, 167.49)

Figure 16: Exp. I (Before Learning NV) Confidence Intervals of Average Order Quantity

The subjects' average order quantities under the high cost high initial wealth (C+W+) condition of 114.84 units had a percentage deviation of 53.1% more than EOQ.

The average order quantities under low cost high initial wealth (C-W+) condition was 69.56 units less than the profit maximizing EOQ of 225 units.

Table 7 presents the variability in subjects' order quantities under various treatment conditions. The standard deviation of the subjects' order quantities (55.64) was smaller than the standard deviation of the actual demand (77.69) or the theoretical standard deviation of the demand (75.0).

Table 7: Exp. I (Before Learning NV) Standard Deviation of NV Order Quantity

Treatment Conditions	Standard Deviation of Order Quantity
C-W+	51.08
C+W+	48.66
C+W-	32.33
C-W-	53.49
ALL	55.64

The analysis of subjects ordering behavior as a function of wealth shows that the subjects' preference is consistent with a utility model of a decreasing loss-aversion (DLA), a decreasing absolute risk-aversion (DARA) or a DARA-DLA newsvendor and is contradictory to the utility model of a risk-neutral, a risk-seeking, a CARA, a IARA, a ILA, or a CLA newsvendor.

5.1.2.3 Adjustment of order quantity

This section presents adjustment in newsvendor decision-making as a function of time, wealth, and demand. The statistical analyses indicate subjects make significant adjustments to their order quantities as their wealth changes and as they gather more experience over time.

Adjustment over time

For these subjects, the order quantity specified by the NV with low initial wealth (C+W-, 2.84 units / period, p-value <0.05 and C-W-, 2.46 units / period, p-value<0.05) shows a significant increasing trend over time (Figure 17). The order quantity specified by the NV with high initial wealth (C-W+ and C+W+) does not exhibit any significant trend.

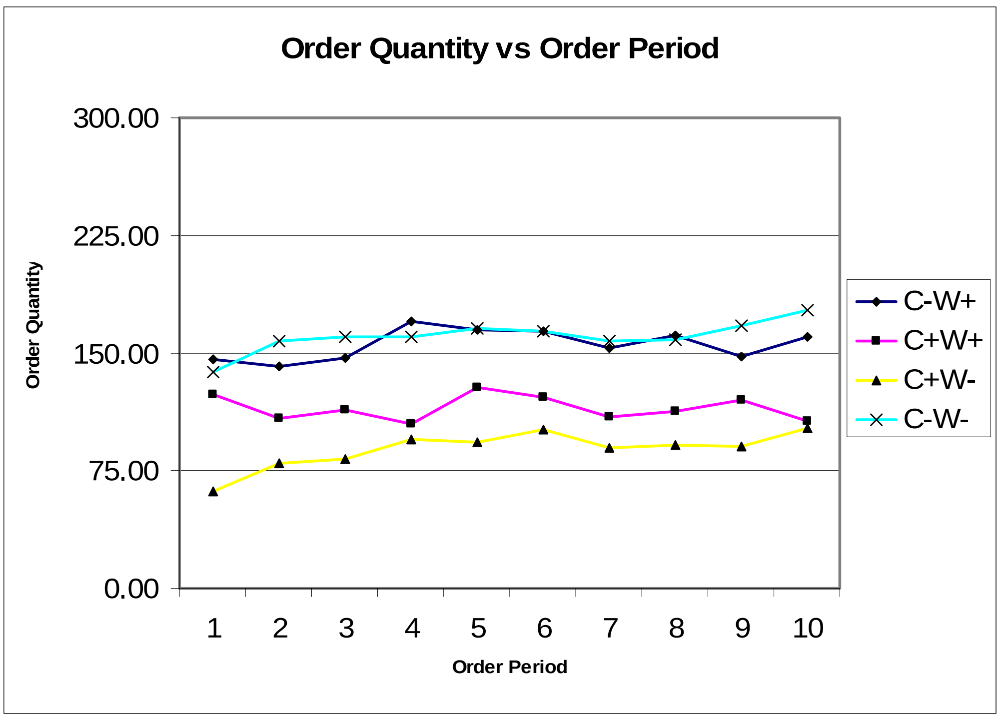

Figure 17: Exp. I (Before Learning NV) Average Order Quantity vs. Order Period

Adjustment over changes in wealth

This section investigates NV decision-making as wealth changes. The plots of the order quantity versus wealth under each treatment condition (Figure 18) suggest the significant correlation between the subjects' order quantity and subjects' wealth. Regression analysis results confirmed that changes in subjects' wealth affected their order quantities under the high cost high wealth condition (C+W+ with p-value < 0.001 and R^2 = 26.9%). No other significant trend was found.

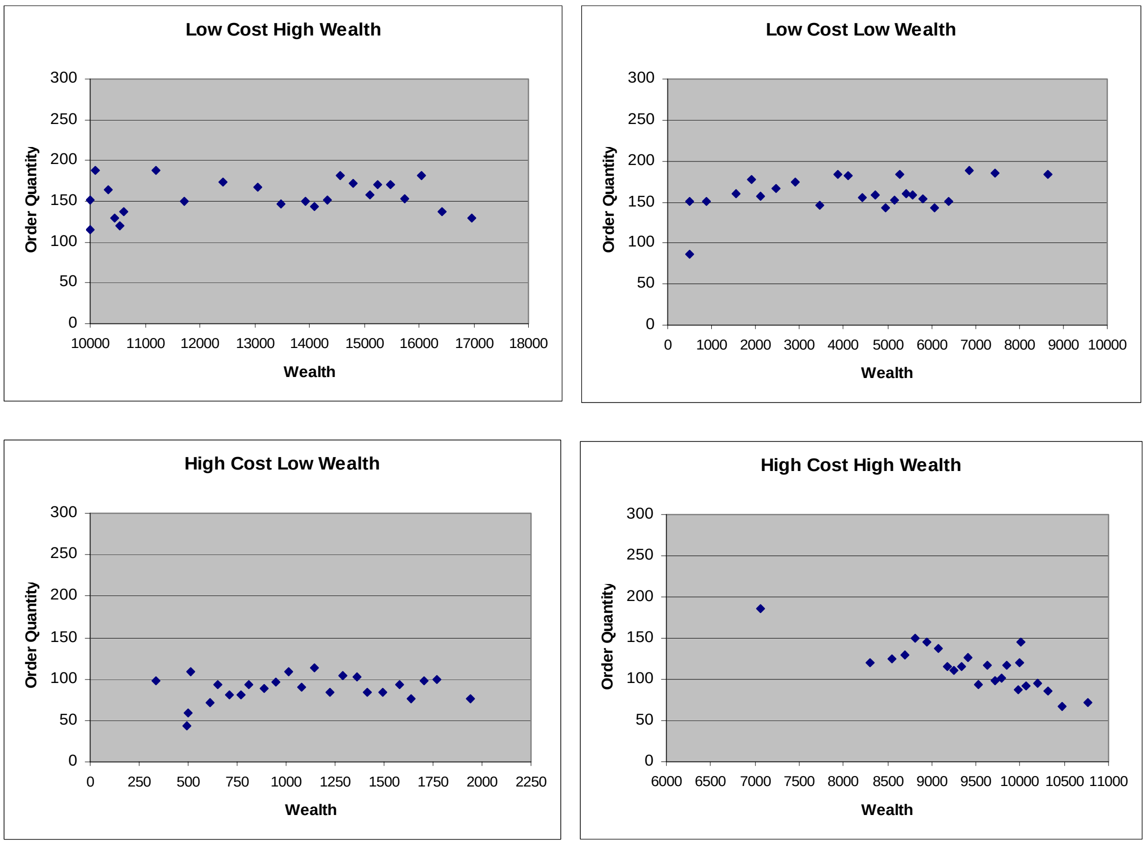

Figure 18: Exp. I (Before Learning NV) Order Quantities vs. Wealth

The NV decision bias resulted in losses for the subjects in C+W+ condition. The expected profit graph (Figure 19) indicates that subjects under high cost (C+) condition are more likely to suffer lose due to deviation from the EOQ (75 units). The average initial order quantity of subjects under C+W+ condition was 123.54 units, which had about 30% chance of loss. Interestingly, the C+W+ Order Quantity vs. Wealth graph (Figure 18) suggests that C+W+ subjects tended to order even more after suffering losses (w < 10000). By increasing the order quantities further away from the EOQ of the low profit item (75 units), subjects are more likely to suffer greater losses. The evidence suggests that newsvendors, after suffering losses, are more likely to engage in a more risky investment to make up for the loss. This risk-seeking after loss behavior of subjects under C+W+ condition is consistent with the Prospect Theory (Kahneman and Tversky, 1979) which predicts risk-seeking preference over loss and risk-aversion preference over gain.

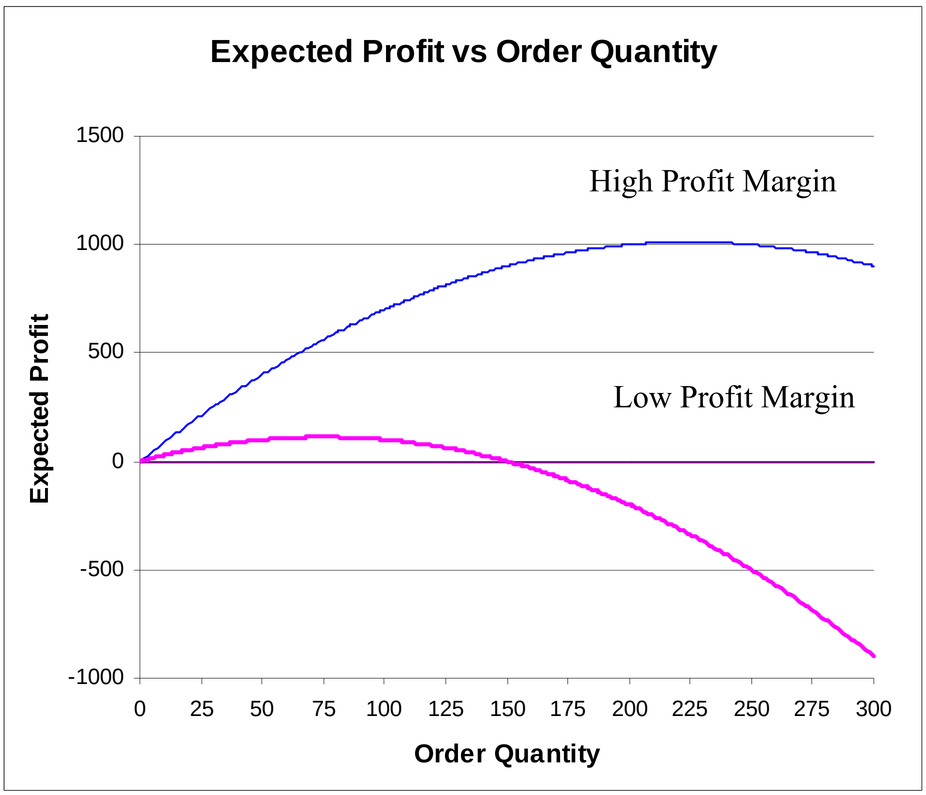

Figure 19: Expected Profit against Order Quantity

Adjustment towards demand

This section presents the analysis of the demand changing heuristics; the tendency to adjust order quantity towards the demand from the previous period. Let the order at period *t* be q_t, and demand at period *t* be d_t. We define the adjustment score at time *t* as:

$$a_t = \frac{q_t - q_{t-1}}{d_{t-1} - q_{t-1}}$$

and 3 types of adjustments as follows:

1. No change from the previous period's order quantity where $a_t = 0$
2. Adjustment towards the previous period's demand where $a_t > 0$
3. Adjustment away from the previous period's demand where $a_t < 0$

The total number of order periods (10) under each treatment condition is divided into three time segments and each segment consists of three ordering periods. Segment 1 consists of orders for periods 2-4, segment 2 consists of orders for periods 5-7, and segment 3 consists of orders for periods 8-10.

Table 8 presents the results of order adjustment analysis over all treatment conditions. Experiment subjects were more likely to change their order quantities in the early periods than in the later periods, especially under the low cost high wealth, and high cost low wealth conditions. These subjects are 2.1 times more likely to adjust their order quantity towards the direction of the previous period's demand than away from the previous demand (*p*-value <0.001). Correlation between q_t-q_{t-1} and q_t-D_{t-1} is significant (r=0.409, *p-value* < 0.05). This correlation test rejects the hypothesis that adjustment in order quantity is not correlated with the difference between previous demand and previous order quantity. Further, 45.8% of individual subjects showed significant demand chasing heuristics.

Table 8: Exp. I (Before Learning NV) Order Quantity Adjustments Summary

C-W+				C+W+			
Period	No Change	Toward	Away	Period	No Change	Toward	Away
2 – 4	27.8%	40.3%	31.9%	2 - 4	47.2%	43.1%	9.7%
5 – 7	38.9%	44.4%	16.7%	5 - 7	48.6%	26.4%	25.0%
8 – 10	50.0%	27.8%	22.2%	8 - 10	41.7%	31.9%	26.4%
C+W-				C-W+			
Period	No Change	Toward	Away	Period	No Change	Toward	Away
2 – 4	38.9%	52.8%	8.3%	2 - 4	50.0%	34.7%	15.3%
5 – 7	55.6%	33.3%	11.1%	5 - 7	51.4%	34.7%	13.9%
8 – 10	55.6%	36.1%	8.3%	8 - 10	45.8%	34.7%	19.4%

Overall			
Period	No Change	Toward	Away
2 - 4	41.0%	42.7%	16.3%
5 - 7	48.6%	34.7%	16.7%
8 - 10	48.3%	32.6%	19.1%
All	45.9%	36.7%	17.4%

5.1.2.4 Newsvendor performance matrix

This section discusses the impact of human decision bias on the total NV profit, shortages, and overages.

Table 9: Exp. I (Before Learning NV) Average Profit or Loss Summary Result

	Decision-makers' Average Profit (Standard Error)	**EOQ Profit**	**Percentage Deviation from EOQ's Profit**
C-W+	7,887.88 (108.23)	8,502.00	-7%[1]
C+W+	-407.88 (322.01)	1,026.00	-140%[1]
C+W-	1,186.25 (108.3)	1,674.00	-29%[1]
C-W-	8,658.00 (222.37)	9,750.00	-11%[1]
Overall	17,324.25 (395.3)	20,952.00	-17%[1]

([1] significant with p-value<0.001)

Table 9 presents the analysis of NV subject's total profit. The average profit of all the subjects in this NV experiment was 17% below the EOQ procurement policy ($t(23)=-9.18$, p-value < 0.001). In the case of low profit margin high initial wealth (C+W+), the NV subjects actually lost money on average due to high decision bias. Even the maximum individual newsvendor profit was less than EOQ profit. This result is consistent with the fact that the EOQ procurement policy outperforms any other ordering policy in the long run.

Table 10 summarizes the shortage and overage of the newsvendor product. For these subjects, the two-sample *t* test results indicate no significant difference between the EOQ policy and the empirical data in terms of overage and shortage per order (p-value >0.19). The average number of units short (39.98) was not significantly different from the average number of units over (35.90) (p-value >0.20) and the difference between the shortage and the overage in the EOQ policy is also insignificant (p-value >0.25). Under the high profit margin (C-) conditions the average number of units over is significantly greater than the average number of units short. Under the low profit margin low wealth (C+W-) condition the average number of units short is more than 5 times greater than the average number of units over. This result is reasonable because the subjects in this experiment tend to order more under low cost (C-) condition than in the high cost (C+) condition.

Table 10: Exp. I (Before Learning NV) Unit Shortage and Overage Summary Result

	Units Short Per Order (Standard Error)	Units Over Per Order (Standard Error)
ALL	39.98 (2.27)	35.90 (2.63)
C-W+	34.41 (3.50)	50.85 (6.57)
C+W+	34.47 (3.80)	32.11 (4.73)
C+W-	62.47 (2.78)	12.30 (4.88)
C-W-	28.58 (5.50)	48.36 (4.36)

5.1.2.5 Human Decision Bias regression analysis of aggregate order quantities

This section presents a regression analysis of Human Decision Bias (HDB) model fitted with the aggregate data of this single newsvendor experiment (Table 11). This approach allows us to estimate the magnitude of the effects of different ordering policies in the HDB model:

$$q_t = p_e \overline{D} + p_u q^* + p_d D_{t-1} + p_q q_{t-1}$$

The first order quantity under each treatment condition was omitted because HDB model is not applicable for t=1.

Table 11: Exp. I (Before Learning NV) HDB Regression Model Input Data

Order	EOQ	d(t-1)	q(t-1)
141.21	225	73	146.33
146.92	225	37	141.21
169.75	225	291	146.92
164.5	225	267	169.75
163.88	225	122	164.5
152.88	225	69	163.88
161.46	225	102	152.88
147.33	225	80	161.46
160.13	225	113	147.33
108.38	75	58	123.54
113.79	75	253	108.38
104.58	75	64	113.79
127.75	75	32	104.58
122.21	75	144	127.75
108.83	75	118	122.21
112.67	75	44	108.83
119.92	75	176	112.67
106.71	75	141	119.92
80.042	75	116	61.875
82.375	75	60	80.042
95.125	75	265	82.375
93.125	75	220	95.125
101.417	75	237	93.125
89.875	75	68	101.417
91.375	75	87	89.875
90.333	75	49	91.375
101.708	75	158	90.333
157.625	225	179	138.042
160.167	225	94	157.625
160.167	225	173	160.167
165.958	225	160	160.167
163.667	225	99	165.958
157.875	225	12	163.667
158.458	225	24	157.875
167.667	225	259	158.458
177.208	225	216	167.667

The HDB model is transformed into a general multivariate linear regression model without loss of generality and is fitted with the empirical data from this experiment. Least square regression gives the best fit HDB model as:

$$q_t = 0.184\overline{D} + 0.173q^* + 0.0442D_{t-1} + 0.558q_{t-1} \quad (1)$$

Regression model checking

Prior to drawing any conclusions from the regression analysis, some standard multivariable linear regression model checks need to be performed.

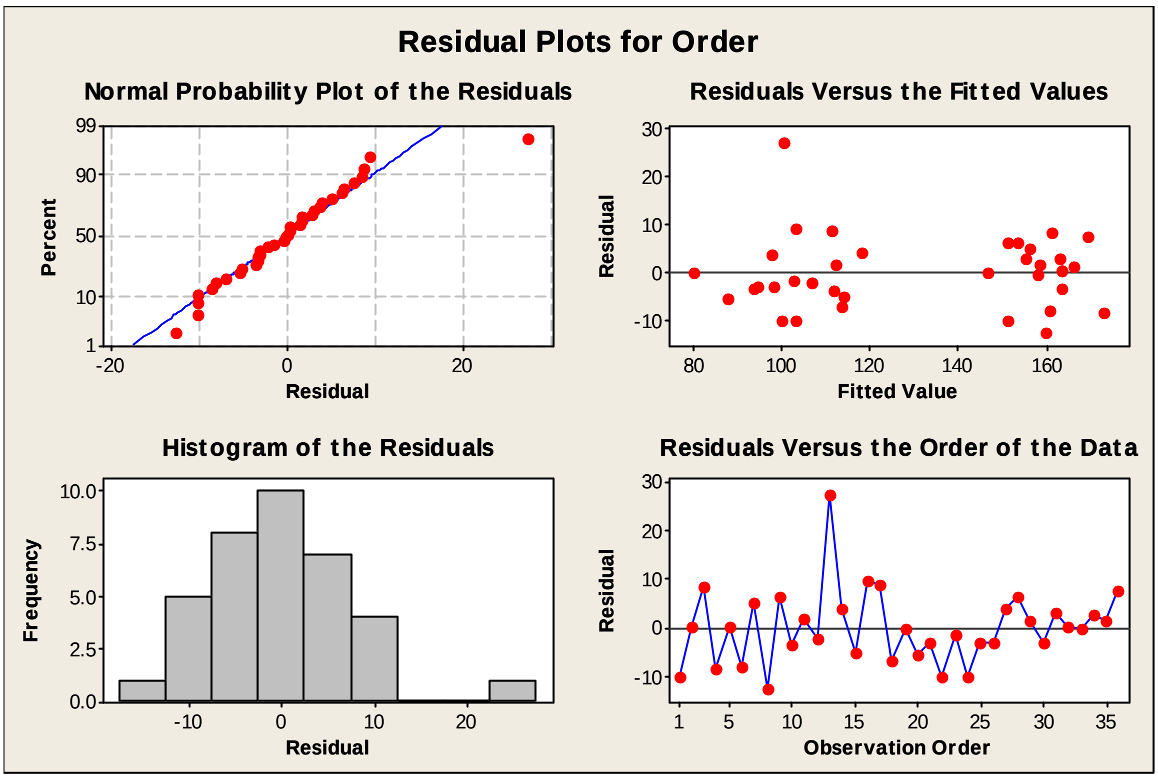

Figure 20: Exp. I (Before Learning NV) Residual Plots of HDB Regression Model

The normality assumption in the linear regression model is important because the parametric tests of hypotheses are robust so long as the distribution of the dependent variable, Y does not depart extremely from normality (Kleinbaum and Kupper 1978). Figure 20 presents a normal probability plot of residuals and a plot of the residual versus the fitted values. These plots appear satisfactory.

Predictor	Coef	SE Coef	T	P
Constant	27.532	8.073	3.41	0.002
EOQ	0.17283	0.03975	4.35	0.000
d(t-1)	0.04419	0.01681	2.63	0.013
q(t-1)	0.55830	0.09659	5.78	0.000

S = 7.88796   R-Sq = 94.1%   R-Sq(adj) = 93.5%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	3	31710	10570	169.88	0.000
Residual Error	32	1991	62		
Total	35	33701			

Source	DF	Seq SS
EOQ	1	29277
d(t-1)	1	354
q(t-1)	1	2079

Durbin-Watson statistic = 2.07538

No evidence of lack of fit (P >= 0.1).

Figure 21: Exp. I (Before Learning NV) Regression Analysis of HDB Model

Another fundamental assumption in the linear regression model is that the error term, ε has zero mean, constant variance, and is not correlated. However, time series data such as our empirical data often violates the correlation assumption. The error terms in time series data often exhibit serial correlation and such error terms are said to be auto-correlated (Montgomery and Peck 1982). Using the standard autocorrelation test developed by Durbin and Watson (1950, 1951, and 1971) we reject the hypothesis that our empirical data exhibited autocorrelation because the Durbin-Watson statistic of 2.075, as indicated in Figure 21, is greater than the critical value for four predictors and a 40 sample size set, $d_U(4,40,0.05)$ of 1.74. The absence of autocorrelation allows application of t and F hypotheses tests for the significance of predictors, thus enabling the validation of hypotheses stated in previous chapters.

Finally, we will check the strength of the linear relationship between the dependant variable and the predictors and the appropriateness of a linear model. The square of the sample correlation coefficient, r, is often used to measure the strength of linear relationship between Y and its predictors in general linear regression model. We have a high R^2 value of 93.5% (Figure 21) which suggests that a large portion of variation in the model is explained by the model predictors. The lack of fit test is used to test for the appropriateness of a linear model. Our lack of fit test result (Figure 21) shows no evidence of significant lack of fit (p>=0.1). We therefore conclude that adding additional terms to the model may not be necessary to adequately explain the variation, and that a linear model is appropriate to describe the relationship between the newsvendor order quantity and these four ordering policies based on available data.

<u>HDB hypotheses testing</u>

The HDB model is a weighted sum of four independent NV procurement policies whose significance in the context of single NV prior to NV training is tested here. For these subjects, the hypotheses tests results confirm the significance of some NV procurement policies and disapprove the significance of others.

HDB model regression analysis results in Figure 21 show that the predictor, D has a coefficient of 0.18355 ($\hat{p}_e$>0) and a t-test statistics of 3.41. Since the value of $t_{0.05,35}$ = 1.69, we have $t_0 > t_{\alpha/2,35}$. Therefore, we reject the null hypothesis of the expected demand hypothesis (5.1) which states

$$H_0 : p_e \leq 0$$

$$H_1 : p_e > 0$$

and conclude with a 90% confidence level that the subjects used the expected demand policy to determine their order quantities.

HDB model regression analysis results in Figure 21 show that the predictor, *EOQ* has a coefficient of 0.17284 ($\hat{p}_u$>0) and a *t*-test statistics of 4.35. Since the value of $t_{0.05,35}$ = 1.69, we have $t_0 > t_{\alpha/2,35}$. Therefore, we reject the null hypothesis of the utility model policy hypothesis (5.2) which states

$$H_0 : p_u \le 0$$

$$H_1 : p_u > 0$$

and conclude with a 90% confidence level that the subjects used the utility model policy to determine their order quantities.

HDB model regression analysis results in Figure 21 show that the predictor, D_{t-1} has a coefficient of 0.04419 ($\hat{p}_d$>0) and a *t*-test statistics of 2.63. Since the value of $t_{0.05,35}$ = 1.69, we have $t_0 > t_{\alpha/2,35}$. Therefore, we reject the null hypothesis of the demand chasing hypothesis (5.3) which states

$$H_0 : p_d \le 0$$

$$H_1 : p_d > 0$$

and conclude with a 90% confidence level that the subjects adjusted their order quantities toward the previous period's demand.

HDB model regression analysis results in Figure 21 show that the predictor, q_{t-1} has a coefficient of 0.55829 ($\hat{p}_q$>0) and a *t*-test statistics of 5.78. Since the value of $t_{0.05,35}$ = 1.69, we have $t_0 > t_{\alpha/2,35}$. Therefore, we reject the null hypothesis of the demand chasing hypothesis (5.4) which states

$$H_0 : p_q \leq 0$$

$$H_1 : p_q > 0$$

and conclude with a 90% confidence level that the subjects anchored their order quantity on the previous period's order quantity.

Table 12: Exp. I (Before Learning NV) Individual Subject HDB Fit Summary Results

Subject	p_e	p_u	p_d	p_q	*sum*
1	0.264	0.243	-0.0807	0.48	0.9063
2	0.43	0.568	-0.156	0.003	0.845
3	0.253	0.286	0.126	0.171	0.836
4	0.429	0.0349	-0.0144	0.507	0.9565
5	0.592	0.167	0.137	0.038	0.934
6	0.383	0.209	-0.032	0.451	1.011
7	0.413	0.172	-0.194	0.652	1.043
8	0.173	0.15	0.191	0.375	0.889
9	0.127	0.172	0.23	0.393	0.922
10	0.34	0.171	0.224	0.292	1.027
11	0.404	0.246	0.114	-0.091	0.673
12	0.119	0.243	0.132	0.474	0.968
13	0.423	0.0742	0.0569	0.163	0.7171
14	0.536	0.0623	0.0699	0.133	0.8012
15	0.303	0.113	0.225	0.182	0.823
16	0.238	0.106	0.105	0.524	0.973
17	0.417	0.429	-0.226	0.187	0.807
18	0.273	0.0217	-0.0737	0.75	0.971
19	0.625	0.181	0.053	0.332	1.191
20	0.295	0.283	-0.174	0.436	0.84
21	-0.0751	0.446	0.0683	0.492	0.9312
22	-0.048	0.252	0.21	0.519	0.933
23	0.0168	0.167	0.0441	0.725	0.9529
24	0.0447	0.589	0.0348	0.246	0.9145
Average	0.290642	0.224421	0.044592	0.351417	0.911071

Table 12 presents the HDB parameter estimates of individual subject. It is interesting that almost all the coefficients are positive, which means that the order quantity of most subjects is affected in a similar manner. For example, the coefficients of

p_u are positive for all 24 subjects, which means all subjects increase their order quantities when under the condition of higher profit margin.

The HDB model completeness hypothesis which states:

$$H_0 : p_e + p_u + p_d + p_q = 1$$

$$H_1 : p_e + p_u + p_d + p_q \neq 1$$

tests if sum of the coefficients in the HDB model equals to 1, implying individual subject's order quantity is a weighted average of four ordering policies. A one sample *t*-test result (Figure 22) rejects the null hypothesis and we conclude with 95% confidence level that the sum of coefficient for the HDB model prior to learning NV does not equal to 1. This result indicates that the subjects' order quantity is not a weighted average of the four alternative NV requisition policies in the HDB model.

```
Test of mu = 1 vs not = 1

N      Mean     StDev   SE Mean          95% CI             T      P
24  0.911071  0.109493  0.022350  (0.864836, 0.957305)  -3.98  0.001
```

Figure 22: Exp. I (Before Learning NV) *t*-test on Sum of Coefficients of HDB Model

5.1.3 Experiment I Results and Analysis (Post Learning NV)

This Section presents the statistical analyses of Experiment I after student subjects received formal training in NV problem.

Students showed understanding of the NV problem after going through classroom NV problem training. Students were assigned non trivial NV problem exercises over a span of 2 weeks to practice mathematical solution of the theoretical newsvendor problem. Various discrete and continuous demand distributions and NV cost structures were included in these exercises. The results of these exercises were mostly satisfactory. According to the teaching assistant, 90% of students scored perfect in these exercises and the remaining 10% made a few calculation mistakes during problem solution. Experiment I was conducted one week after the last class learning exercise on newsvendor problem was conducted. We recruited 22 subjects from previous round to repeat in the same NV experiment. We present the statistical analyses of the data collected from this experiment in five major categories:

1. Factorial design experiment analyses.
2. Analyses of mean and variance of NV order quantity.
3. Analyses of NV order quantity adjustments over time and wealth.
4. Analyses of NV performance in term of profits, shortages, and overages.
5. Hypotheses testing of the HDB model.

5.1.3.1 Factorial design experiment analyses

This factorial experiment analysis investigates the significance of the NV's initial wealth term and the item profit margin term on newsvendor order quantities after subjects receive a formal training on NV problem. The average order quantity of all subjects from each treatment level replication was compiled in such a way that each treatment condition has 10 data points. Figure 23 presents the normal probability plot of residuals. Other than some slight tail effects, the data appears normal.

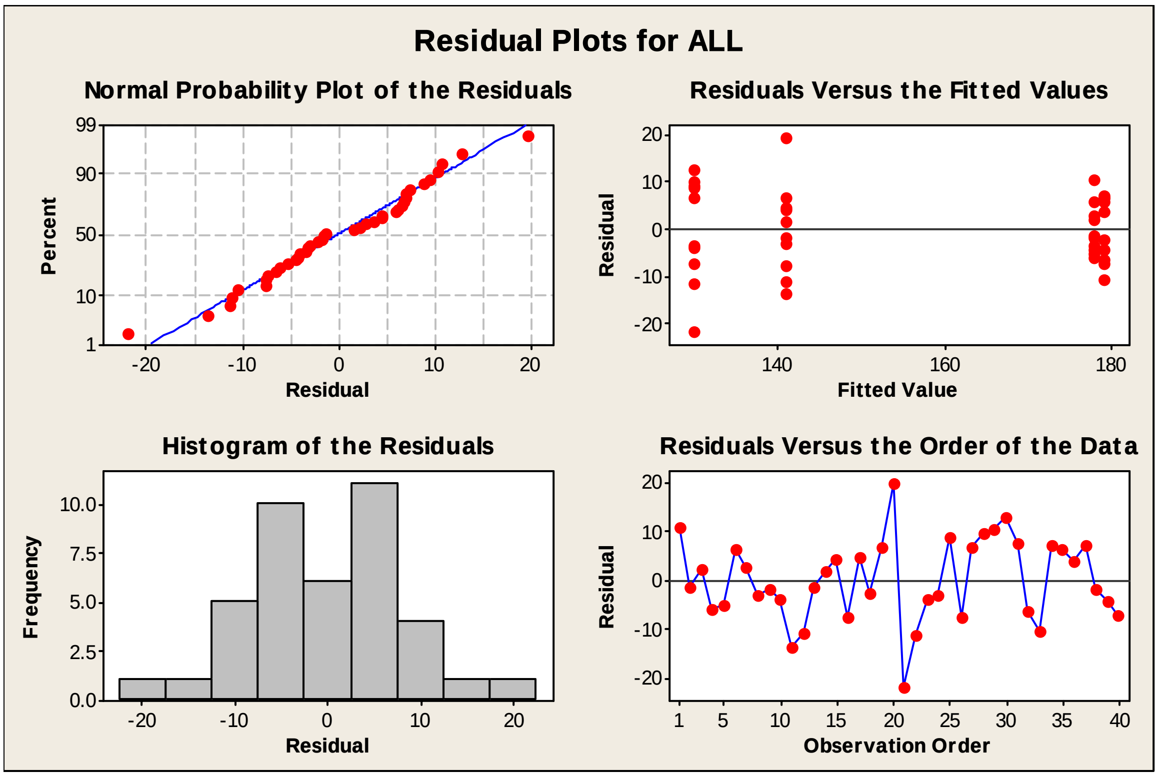

Figure 23: Exp. I (Post Learning NV) Normal Probability Plot of the Residuals

Average order quantity

This factorial design experiment is set up and analyzed in the MINITAB version 14 software. Figure 24 displays the effect estimates, the regression coefficients, and the sum of squares for each main effect and interaction terms. For these subjects, this statistical analysis indicates the initial wealth, the item profit margin, and the interaction between these 2 factors to significantly affect newsvendor order quantity. The estimated effects for the aggregate data set shows the initial wealth term had positive effect of 4.90 which means higher order quantity is achieved at the high initial wealth level. The estimated effects for the cost term is -43.16 which means the decision-makers ordered less under higher cost conditions than under lower cost conditions.

Estimated Effects and Coefficients for ALL (coded units)

Term	Effect	Coef	SE Coef	T	P
Constant		156.97	1.379	113.85	0.000
Wealth	4.90	2.45	1.379	1.78	0.084
Cost	-43.16	-21.58	1.379	-15.65	0.000
Wealth*Cost	6.05	3.02	1.379	2.19	0.035

Analysis of Variance for ALL (coded units)

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Main Effects	2	18870.6	18870.6	9435.32	124.10	0.000
2-Way Interactions	1	365.5	365.5	365.48	4.81	0.035
Residual Error	36	2737.2	2737.2	76.03		
Pure Error	36	2737.2	2737.2	76.03		
Total	39	21973.3				

Figure 24: Exp. I (Post Learning NV) Factorial Design Analysis and ANOVA Summary

For these data, the cost and initial wealth interaction plot (Figure 25) shows that initial wealth effect is very small when the cost is low (C-) and very large when the cost is high (C+). This interaction plot also shows that the cost effect is large when initial wealth is low or high. Therefore, we can conclude that initial wealth effect affects newsvendor decision-making most when item cost is high and that the item profit margin effect affects newsvendor decision-making regardless of the levels of newsvendor's initial wealth.

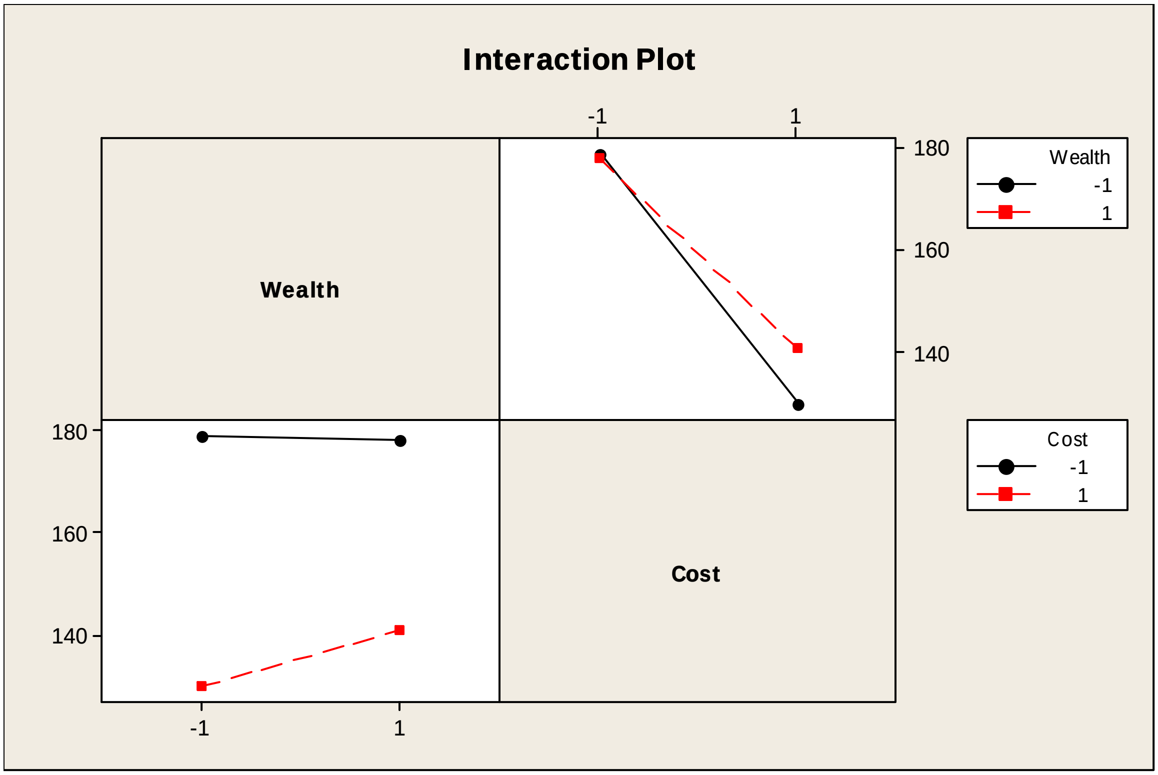

Figure 25: Exp. I (Post Learning NV) Interaction Plots

Individual order quantity

This section investigates the percentage of NV subjects whose decision-making is influenced by either the item cost term or the initial wealth term. The analysis results (Table 13) show that 83.36% of the subjects were influenced by at least one of the main factors. The item profit margin and the initial wealth factors affected the decisions of 77.27% and 45.45% of the subjects respectively.

Table 13: Exp. I (Post Learning NV) Summary of Percentage of Participants with Significant Factors

Factor	Significant	Not Significant
Cost	77.27%	22.73%
Wealth	45.45%	54.55%
Either one	86.36%	13.64%

5.1.3.2 Descriptive statistics of NV order quantity

The results of the one sample *t*-test comparisons of the average order quantity and the expected demand (150) confirmed that order quantities in treatment conditions C-W- ($t(219)=8.60$, *p*-value < 0.001), C-W+ ($t(219)=8.92$, *p*-value < 0.001), C+W- ($t(219)=-4.93$ *p*-value <0.001), and C+W+ ($t(219)=-2.66$ *p*-value < 0.01) significantly deviated from the expected demand. The order quantities under low cost (C-) conditions deviated most significantly from the expected demand (150).

For these subjects, the one sample *t*-test results indicate the order quantities under all four treatment conditions exhibit significant deviation from their respective profit maximizing EOQs. On average, the average inventory orders of subjects who faced high cost conditions were above the expected profit maximizing order quantity of 75; C+W- ($t(219)=13.47$ *p*-value <0.001), and C+W+ ($t(219)=19.19$ *p*-value < 0.01). On average, the average inventory orders of subjects who faced low cost conditions were below the expected profit maximizing order quantity of 225; C-W- ($t(219)=-13.54$, *p*-value < 0.001) and C-W+ ($t(219)=-14.99$, *p*-value < 0.001).

The average order quantities under the high cost high initial wealth (C+W+) condition of 114.84 units had a percentage deviation of 87.8% more than EOQ. The average order quantities under low cost high initial wealth (C-W+) condition was 47.02 units less than the profit maximizing EOQ of 225 units.

Table 14 presents the variability in decision-makers' order quantities under various treatment conditions. The standard deviation of the subjects' order quantities (55.64) was smaller than the standard deviation of the actual demand (77.69) or the theoretical standard deviation of the demand (75.0). This result seems to contradict the commonly known Bullwhip Effect in inventory systems, where variation is amplified upstream in a supply chain. This topic will be further discussed more in the multi-echelon NV setting later.

Table 14: Exp. I (Post Learning NV) Standard Deviation of NV Order Quantity

Treatment Conditions	Standard Deviation of Order Quantity
C-W+	46.54
C+W+	50.90
C+W-	60.46
C-W-	50.24
ALL	56.62

The analysis of subjects ordering behavior as a function of wealth shows that the subjects' preference is consistent with a utility model of a decreasing loss-aversion (DLA), a decreasing absolute risk-aversion (DARA) or a DARA-DLA newsvendor and is contradictory to the utility model of a risk-neutral, a risk-seeking, a CARA, a IARA, a ILA, or a CLA newsvendor.

5.1.3.3 Adjustment of order quantity

This Section presents adjustment in newsvendor decision-making as a function of time, wealth, and demand. The statistical analyses indicate subjects make significant adjustments to their order quantities as their wealth changes and as they gather more experience over time.

Adjustment over time

The order quantity of the newsvendor in low profit margin (C+W-, 3.32 units / period, *p*-value <0.005 and C+W+, 2.52 units / period, *p*-value<0.01) shows a significant increasing trend over time (Figure 26). The order quantity of the newsvendor in high profit margin conditions (C-W+ and C-W-) does not exhibit any significant trend.

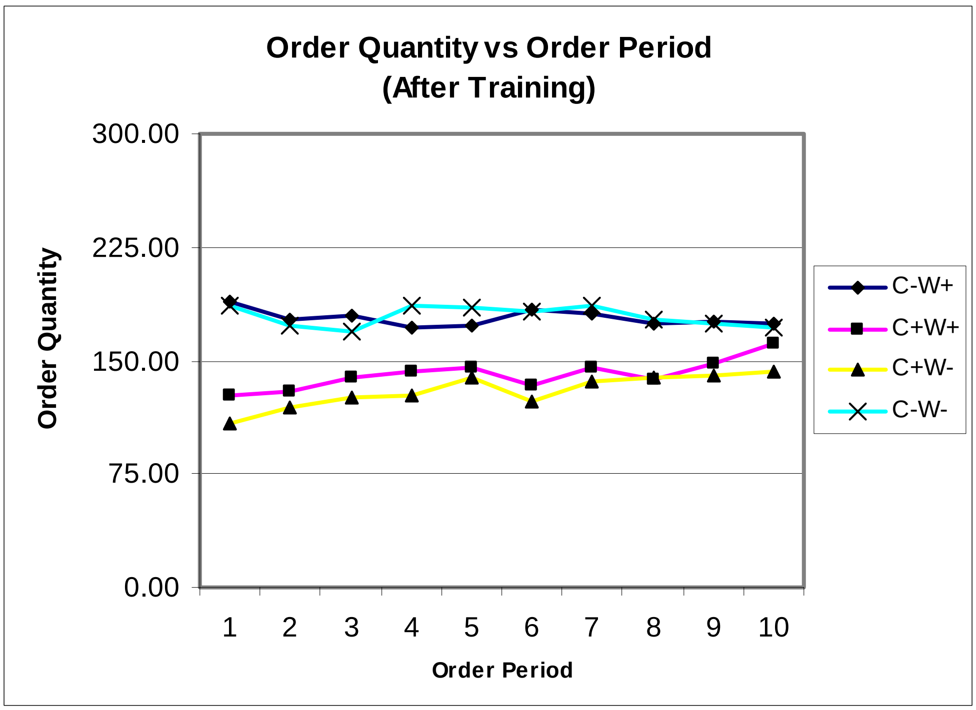

Figure 26: Exp. I (Post Learning NV) Average Order Quantity vs. Order Period

Adjustment over changes in wealth

This section investigates NV decision-making as wealth changes. The plots of the order quantity versus wealth under each treatment condition (Figure 27) suggest the significant correlation between the order quantity and wealth. Regression analysis results confirmed that changes in subjects' wealth affected their order quantities under the high cost high initial wealth condition (C+W+ with p-value < 0.001 and R^2 = 32.2%) and under the low cost low initial wealth condition (C-W- with p-value < 0.05 and R^2 = 22.9%). No other significant trend was found.

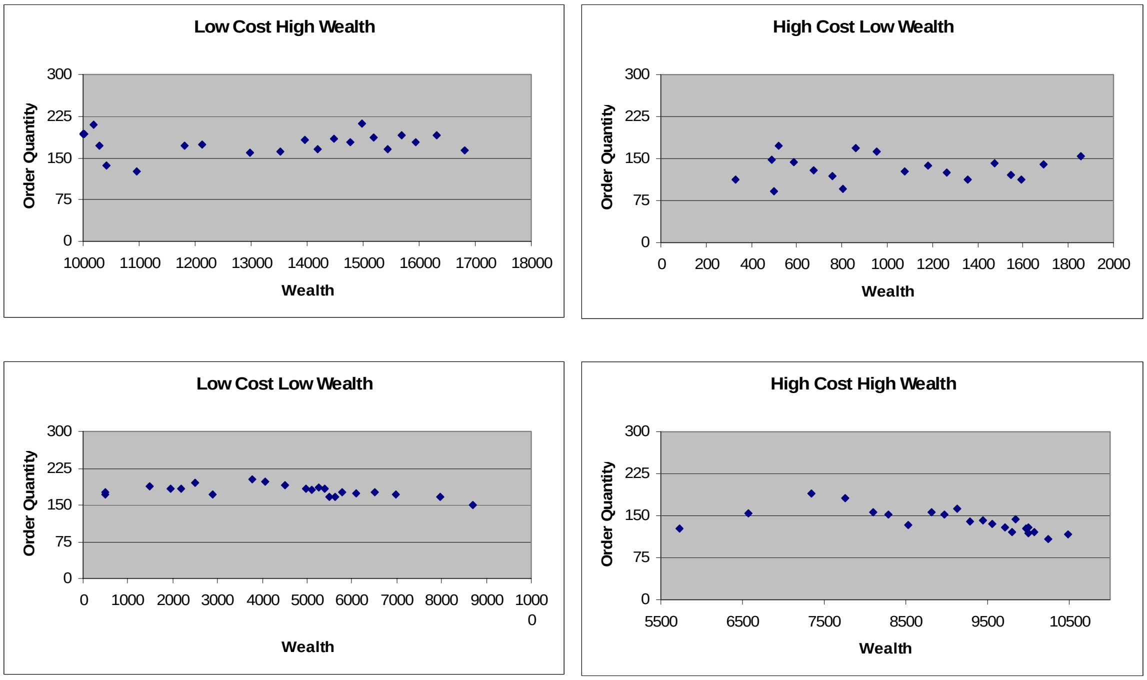

Figure 27: Exp. I (Post Learning NV) Order Quantities vs. Wealth

The newsvendor decision bias caused the subjects in C+W+ condition to lose money. The probability of loss versus order quantity graph (Figure 28) indicates that subjects under high cost (C+) condition are more likely to suffer loss due to deviation from the EOQ (75 units). The average initial order quantity of subjects under C+W+ condition was 140.86 units, which had about 35% chance of loss. Interestingly, the C+W+ Order Quantity vs. Wealth graph (Figure 27) suggests that C+W+ subjects tended to order even more after suffering losses (w < 10000). The evidence would suggest that newsvendors, after suffering losses, are more likely to engage in a more risky investment to make up for the loss. This ordering behavior of subjects under C+W+ condition is consistent with the Prospect Theory (Kahneman and Tversky, 1979) which predicts risk-seeking preference over loss and risk-aversion preference over gain.

Figure 28: Probability of Loss against Order Quantity

Adjustment towards demand

This section presents our analysis of the demand changing heuristics; the tendency to adjust order quantity towards the demand from the previous period. Table 15 presents the results of order adjustment analysis over all treatment conditions. Decision-makers were more equally likely to change the order quantity in the early periods and in the later periods. Decision-makers are 2.37 times more likely to adjust their order quantity towards the direction of the previous period's demand than away from the previous demand (p-value <0.001). Correlation between q_t-q_{t-1} and q_t-D_{t-1} is not significant (r=0.266, p-value = 0.266). This correlation test fails to reject the hypothesis that adjustment in order quantity is not correlated with the difference between previous demand and previous order quantity. Further, 45.5% of individual subjects showed significant demand chasing heuristics.

Table 15: Exp. I (Post Learning NV) Order Quantity Adjustments Summary

C-W+				C+W+			
C-W+	No Change	Toward	Away	C+W+	No Change	Toward	Away
2 - 4	51.5%	34.8%	13.6%	2 - 4	36.4%	43.9%	19.7%
5 - 7	42.4%	39.4%	18.2%	5 - 7	39.4%	47.0%	13.6%
8 - 10	43.9%	40.9%	15.2%	8 - 10	40.9%	39.4%	19.7%
C+W-				C-W+			
Period	No Change	Toward	Away	Period	No Change	Toward	Away
2 - 4	45.5%	37.9%	16.7%	2 - 4	39.4%	37.9%	22.7%
5 - 7	45.5%	37.9%	16.7%	5 - 7	50.0%	36.4%	13.6%
8 - 10	40.9%	42.4%	16.7%	8 - 10	45.5%	39.4%	15.2%

Overall			
Period	No Change	Toward	Away
2 - 4	41.0%	42.7%	16.3%
5 - 7	48.6%	34.7%	16.7%
8 - 10	48.3%	32.6%	19.1%
All	45.9%	36.7%	17.4%

5.1.3.4 Newsvendor performance matrix

This section discusses the impact of human decision bias on the total NV profit, shortages, and overages.

Table 16: Exp. I (Post Learning NV) Average Profit or Loss Summary Result

	Decision-makers' Average Profit (Loss)	EOQ's Profit (Loss)	Percentage Deviation from EOQ's Profit
C-W+	10,625.59 (181.4)	11,274.00	-6%[1]
C+W+	-1,193.32 (288.8)	702.00	-270%[1]
C+W-	-1,396.64 (552.0)	534.00	-362%[1]
C-W-	7,576.91 (137.4)	7,674.00	-1%
Overall	15,612.55 (865.5)	20,184.00	-23%[1]

([1] significant with p-value<0.005)

Table 16 presents the analysis of newsvendor profit. The average profit of all the decision-makers in this NV experiment was 23% below the EOQ procurement policy ($t(21)=-5.28$, p-value < 0.001). In the case of low profit margin (C+W-,C+W+), the decision-makers actually lost money on average due to high decision bias. Unlike the results from previous round, one subject with profit of $20,422 actually outperformed the EOQ policy and another subject followed EOQ policy exactly.

Table 17 summarizes the shortage and overage of the newsvendor product. The two-sample t test results indicate no significant difference between the EOQ policy and the empirical data in terms of the overage per order or the shortage per order (p-value >0.53). The average number of units short (32.56) were significantly less than the average number of units over (51.35) (p-value < 0.001), while the difference between the shortage and the overage in the EOQ policy is insignificant (p-value >0.45). Under the high profit margin (C-) conditions the average number of units over is significantly greater than the average number of units short. Under the low profit margin low wealth (C-W-) condition the average number of units over is more than 5 times greater than the average number of units short.

Table 17: Exp. I (Post Learning NV) Unit Shortage and Overage Summary Result

	Units Short Per Order (Standard Error)	Units Over Per Order (Standard Error)
ALL	32.56 (2.62)	51.35 (3.01)
C-W+	24.06 (4.35)	44.94 (5.30)
C+W+	52.90 (5.42)	45.16 (5.71)
C+W-	41.00 (6.24)	44.12 (3.69)
C-W-	12.28 (2.62)	71.20 (3.01)

5.1.3.5 HDB regression analysis of aggregate order quantities

This Section presents a regression analysis of HDB model fitted with the aggregate data of this single newsvendor experiment (Table 18). This approach allows us to estimate the magnitude of the effects of different ordering policies in the HDB model:

$$q_t = p_e \overline{D} + p_u q^* + p_d D_{t-1} + p_q q_{t-1}$$

The first order quantity under each treatment condition was omitted because HDB model is not applicable for t=1.

Table 18: Exp. I (Post Learning NV) HDB Regression Model Input Data

Order	EOQ	d(t-1)	q(t-1)
176.636	225	94	188.682
180.273	225	183	176.636
171.864	225	116	180.273
172.773	225	41	171.864
184.136	225	211	172.773
180.727	225	294	184.136
174.682	225	162	180.727
176.182	225	102	174.682
173.818	225	213	176.182
129.773	75	37	127.182
139.273	75	288	129.773
142.455	75	213	139.273
145.273	75	253	142.455
133.227	75	126	145.273
145.364	75	285	133.227
137.909	75	129	145.364
147.545	75	28	137.909
160.591	75	96	147.545
118.5	75	94	107.955
125.909	75	218	118.5
126.591	75	193	125.909
138.727	75	101	126.591
122.409	75	6	138.727
136.636	75	107	122.409
139.409	75	196	136.636
140.227	75	19	139.409
142.818	75	57	140.227
172.636	225	201	186.5
168.545	225	203	172.636
186.136	225	47	168.545
185.182	225	32	186.136
182.864	225	166	185.182
186.091	225	196	182.864
177	225	57	186.091
174.591	225	158	177
171.727	225	108	174.591

The HDB model is transformed into a general multivariate linear regression model without loss of generality and is fitted with the empirical data from this experiment. Least square regression gives the best fit HDB model as:

$$q_t = 0.401\overline{D} + 0.114q^* + 0.0097D_{t-1} + 0.504q_{t-1} \qquad (2)$$

Regression model checking

Prior to drawing any conclusions from the regression analysis, some standard multivariable linear regression model checks need to be performed.

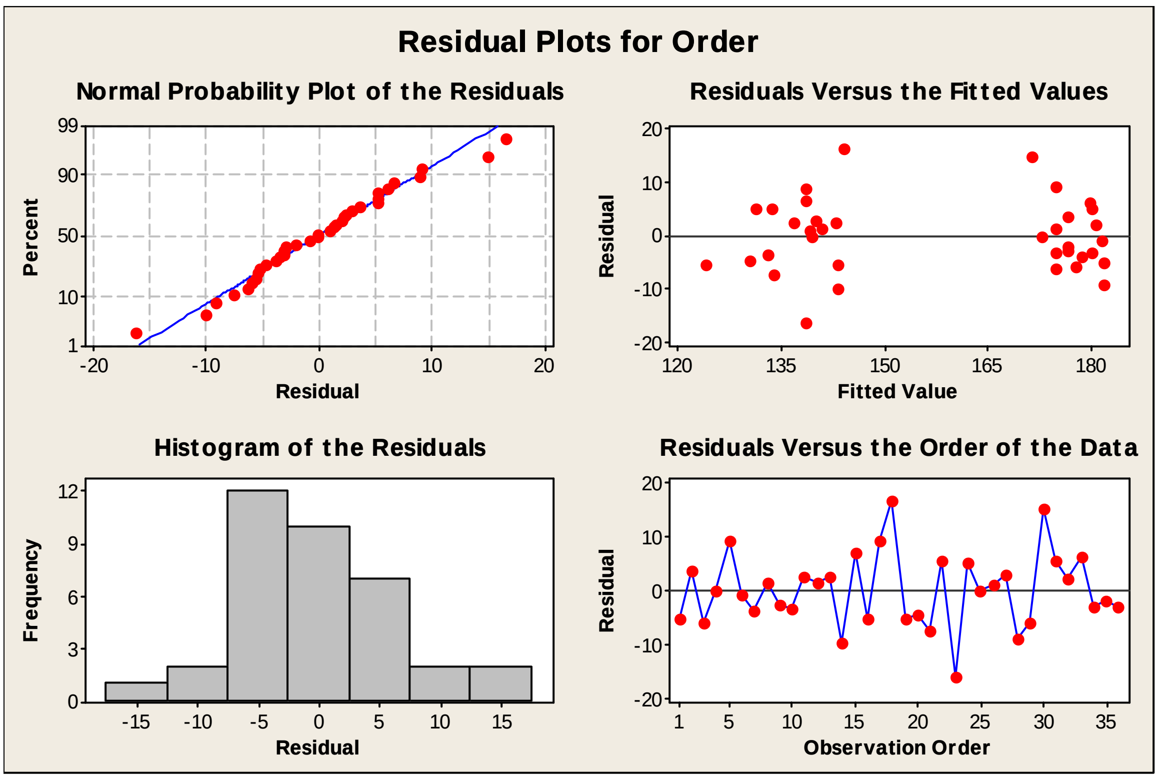

Figure 29: Exp. I (Post Learning NV) Residual Plots of HDB Regression Model

The normality assumption in the linear regression model is important because the parametric tests of hypotheses are robust so long as the distribution of the dependent variable, *Y* does not depart extremely from normality (Kleinbaum and Kupper 1978). Figure 29 presents a normal probability plot of residuals and a plot of the residual versus the fitted values. These plots appear satisfactory.

```
Predictor     Coef  SE Coef     T      P
Constant     60.14    16.10  3.74  0.001
EOQ        0.11399  0.04592  2.48  0.018
d(t-1)     0.00968  0.01474  0.66  0.516
q(t-1)      0.5043   0.1417  3.56  0.001

S = 7.10271   R-Sq = 90.4%   R-Sq(adj) = 89.5%

Analysis of Variance

Source          DF       SS      MS       F      P
Regression       3  15182.9  5061.0  100.32  0.000
Residual Error  32   1614.4    50.4
Total           35  16797.2

Source  DF   Seq SS
EOQ      1  14529.4
d(t-1)   1     14.3
q(t-1)   1    639.2

Durbin-Watson statistic = 2.31707

No evidence of lack of fit (P >= 0.1).
```

Figure 30: Exp. I (Post Learning NV) Regression Analysis of HDB Model

Another fundamental assumption in the linear regression model is that the error term, ε has zero mean, constant variance, and is not correlated. However, time series data such as our empirical data often violates the correlation assumption. The error terms in time series data often exhibit serial correlation and such error terms are said to be auto-correlated (Montgomery and Peck 1982). Using the standard autocorrelation test developed by Durbin and Watson (1950, 1951, and 1971) we reject the hypothesis that our empirical data exhibited autocorrelation because the Durbin-Watson statistic of 2.317, as indicated in Figure 30, is greater than the critical value for 4 predictors and 40 sample set, $d_U(4,40,0.05)$ of 1.74. The absence of autocorrelation permitted the used of t and F statistics to test the significance of predictors, thus enabling the validation of hypotheses stated in previous chapters.

Finally, we will check the strength of linear relationship between the dependent variable and the predictors and the appropriateness of a linear model. The square of the sample correlation coefficient, *r*, is often used to measure the strength of linear relationship between *Y* and its predictors in general linear regression model. We have a high R^2 value of 90.4% (Figure 30) which suggests that most variation in the model is explained by the model predictors. The lack of fit test is used to test for the appropriateness of a linear model. Our lack of fit test result (Figure 30) shows no evident of significant lack of fit (p>=0.1). We therefore conclude that adding additional terms to the model is not really necessary, and that a linear model is appropriate to describe the relationship between the newsvendor order quantity and these four ordering policies based on available data.

<u>*HDB hypotheses testing*</u>

The HDB model is a weighted sum of four independent NV procurement policies whose significance in the context of single NV prior to NV training is tested here. Hypotheses tests results will confirm the significance of some NV procurement policies and disapprove the significance of others.

HDB model regression analysis result in Figure 30 shows that the predictor, *D* has a coefficient of 0.401 ($\hat{p}_e$>0) and a *t*-test statistics of 3.74. Since the value of $t_{0.05,35}$ = 1.69, so we have $t_0 > t_{\alpha/2,35}$. Therefore, we reject the null hypothesis of the expected demand hypothesis (5.1) which states

$$H_0 : p_e \leq 0$$

$$H_1 : p_e > 0$$

and conclude with a 90% confidence level that decision-makers used the expected demand policy to determine their order quantities.

HDB model regression analysis result in Figure 30 shows that the predictor, *EOQ* has a coefficient of 0.114 ($\hat{p}_u$ >0) and a *t*-test statistics of 2.48. Since the value of $t_{0.05,35}$ = 1.69, so we have $t_0 > t_{\alpha/2,35}$. Therefore, we reject the null hypothesis of the utility model policy hypothesis (5.2) which states

$$H_0 : p_u \leq 0$$

$$H_1 : p_u > 0$$

and conclude with a 90% confidence level that decision-makers used the utility model policy to determine their order quantities.

HDB model regression analysis result in Figure 30 shows that the predictor, D_{t-1} has a coefficient of 0.010 ($\hat{p}_d$ >0) and a *t*-test statistics of 0.66. Since the value of $t_{0.05,35}$ = 1.69, so we have $t_0 < t_{\alpha/2,35}$. Therefore, we fail to reject the null hypothesis of the demand chasing hypothesis (5.3) which states

$$H_0 : p_d \leq 0$$

$$H_1 : p_d > 0$$

and conclude with a 90% confidence level that decision-makers did not adjust their order quantities toward the previous period's demand.

HDB model regression analysis result in Figure 30 shows that the predictor, q_{t-1} has a coefficient of 0.504 ($\hat{p}_q$ >0) and a *t*-test statistics of 3.56. Since the value of $t_{0.05,35}$ = 1.69, so we have $t_0 > t_{\alpha/2,35}$. Therefore, we reject the null hypothesis of the demand chasing hypothesis (5.4) which states

$$H_0 : p_q \le 0$$

$$H_1 : p_q > 0$$

and conclude with a 90% confidence level that decision-makers anchored their order quantity on the previous period's order quantity.

Table 19: Exp. I (Post Learning NV) Individual Subject HDB Fit Summary Results

Subject	p_e	p_u	p_d	p_q	*Sum*
1	0.139	-0.164	-0.0917	1.13	1.0133
2	0.943	0.0465	-0.0292	0.126	1.0863
3	0.502	-0.0239	-0.0899	0.668	1.0562
4	0.218	0.44	-0.009	0.357	1.006
5	0.539	0.414	0.219	-0.253	0.919
6	0.87	0.796	-0.277	-0.31	1.079
7	0.986	0.274	-0.385	0.192	1.067
8	0.663	0.133	-0.139	0.412	1.069
9	0.746	0.413	0.126	-0.135	1.15
10	1.12	-0.188	-0.537	0.658	1.053
11	0.181	-0.0171	0.286	0.37	0.8199
12	0.475	-0.117	0.253	0.402	1.013
13	0.541	0.323	0.075	0.106	1.045
14	0.392	0.175	0.188	0.246	1.001
15	0.952	0.318	0.0014	-0.27	1.0014
16	0.215	0.102	0.145	0.505	0.967
17	0.444	0.0108	0.467	0.095	1.0168
18	0.182	0.0413	0.132	0.692	1.0473
19	0.448	0.101	-0.266	0.752	1.035
20	0.08	0.0152	0.0633	0.858	1.0165
21	0.0439	0.0142	0.00997	0.925	0.99307
22	0	1	0	0	1
Average	0.48545	0.186682	0.006449	0.342091	1.020671

Table 19 presents the HDB parameter estimates of individual subject. It is interesting that almost all the coefficients are positive, which means that the order quantity of individual newsvendor subject is affected in a similar manner. For example, the coefficients of p_u are positive for most subjects, which means most subjects increase their order quantities with higher profit margin.

The HDB model completeness hypothesis which states

$$H_0 : p_e + p_u + p_d + p_q = 1$$

$$H_1 : p_e + p_u + p_d + p_q \neq 1$$

tests if the sum of the coefficients in the HDB model equals to 1, which implies individual newsvendor order quantity is a weighted average of four NV requisition policies. A one sample *t*-test result (Figure 31) fails to reject the null hypothesis and we conclude with 95% confidence level that the sum of coefficient for the HDB model prior to learning NV equals to 1.

```
Test of mu = 1 vs not = 1

Variable   N     Mean    StDev  SE Mean        95% CI            T      P
After NV  22  1.02067  0.06494  0.01385  (0.99188, 1.04946)  1.49  0.150
```

Figure 31: Exp. I (Post Learning NV) *t*-test on Sum of Coefficients of HDB Model

5.1.4 Experiment I Conclusion

This Section highlights the results of the single NV experiments, conducted with an identical pool of student subjects, before and after the subjects received formal training on newsvendor problem. Table 20 presents a summary of major results before and after NV training.

The first significant result is that a class room training of NV problem prior to the NV experiment does little, if any, in improving newsvendor decision making in terms of reducing human decision bias and improving profits. This ineffectiveness of classroom NV training in improving NV decision-making is somewhat surprising because 90% of the subjects have answered all theoretical NV problems correctly. We observed under the high profit conditions, decision-makers seemed to order closer to the EOQ after learning about NV. However, subjects' average order quantities deviated further from EOQ under the low profit margin conditions.

Second, the human decision bias (HDB) regression analysis of the empirical data supports the anchoring and insufficient adjustment heuristic (Schweitzer and Cachon, 2000) as the cause of human decision bias. The HDB model shows that the effect of the anchoring at the previous order quantity ordering policy is significantly larger than the effect of EOQ order policy before and after subjects received NV training. As a result, subject's subsequent order quantities were significantly anchored at the first order quantity. Since the subject's first order quantity was between the expected demand and the EOQ, with slow or insignificant adjustment towards EOQ, human decision bias persisted. The question is: Why do subjects not adjust?

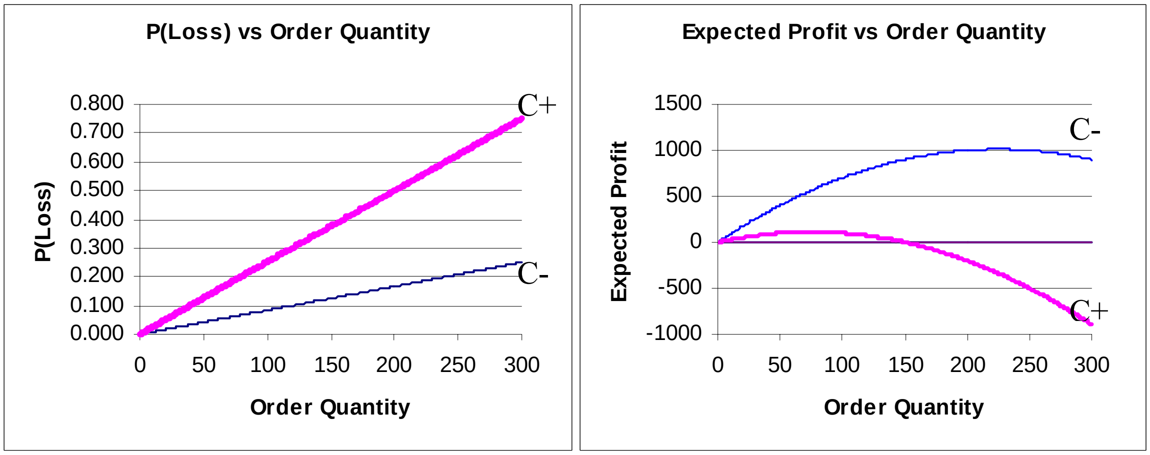

Figure 32: Probability of Loss and Profit vs. Newsvendor Order Quantity

Two reasons may explain the insufficient adjustment effect. First, subjects were content with the profit they were making and did not find it necessary to adjust their order quantities. This is most apparent in high profit margin (C-) conditions where subjects can easily make profit due to low probability of losses and the decreasing rate of expected profit increases. Figure 32 illustrates these characteristics of NV investment in high profit margin item (C-):

1. The probability of loss is relatively low between mean (150) and EOQ (225) which means subjects will make profit more than 80% of the time.
2. The rate of expected profit increase is relatively flat between mean (150) and EOQ (225) which explains subject's reluctance to adjust.

Subjects seem content with the steady growth of wealth and become satisfied with the current order level. They may make small changes in response to demand spikes, but these small adjustments to the order quantities were not significant enough to eliminate human decision bias.

The second reason for the insufficient adjustment is that subjects made wrong adjustments to their order quantities. This is evident in the high wealth high cost (C+W+) condition where the subjects' initial order quantities were significantly higher than EOQ and the subjects were losing money. Subjects then increased their order quantities to make up for losses. Unfortunately, increasing order quantities away from EOQ (75) resulted in greater probability of loss (Figure 32) and lower expected profit. This risk-seeking over loss behavior is best captured by the prediction of the Prospect Theory (Kahneman and Tversky, 1979).

Finally, empirical data seems to support this somewhat counterintuitive notion that given a similar level of wealth and NV investment option, a subject whose wealth is below initial wealth and a subject whose wealth is above initial wealth will invest in different manners. Consider the C+W- and C+W+ subjects in our empirical studies. The order quantities of C+W- subjects were steady over the span of wealth greater than w_o, but the order quantities of C+W+ subjects were increasing over the span of wealth which was less than w_o (i.e. increasing order quantity after loss). If the trends in both treatment conditions are extrapolated by another 20-30 order periods, the low initial wealth subjects would have about the same amount of wealth as the high initial wealth subjects would, but they would order in starkly different manners. This conjecture is consistent to the results of the concert ticket experiment where subjects who have lost a $20 ticket are more likely to go home without watching the concert than those who have lost $20 in cash (Kahneman and Tversky, 2000).

Table 20: Exp. I Result Summary

Analysis	Prior to Training	Post Training	Comments
Profit margin factor	Significant at 95%	Significant at 95%	Profit margin consistently contributed to most of the effects
NV initial wealth factor	Significant at 95%	Significant at 90%	After training, subjects' wealth factor is not as significant as before.
Interaction of profit margin and initial wealth factor	Significant at 95%	Significant at 95%	Wealth effect is significant only in the low profit margin.
Average initial OQ	< 150 for all conditions	< 150 for low profit item, > 150 for high profit item	Subjects showed impact of experience
% of subjects with significant profit margin factor	83.30%	77.27%	No significant changes before and after training
% of subjects with significant wealth factor	37.50%	45.45%	No significant changes before and after training
Significant trend observed in OQ vs. wealth	C+W+	C+W+	Order quantities increased as wealth decreased in C+W+ condition. Risk seeking over loss.
Significant trend observed in OQ vs. time	C+W-, C-W-	C+W+, C+W-	Slope was generally small
Deviation from mean	Significant	Significant	Human decision bias observed
Deviation from profit maximizing EOQ	Significant	Significant	Human decision bias is significant before and after NV training
Average subjects' profit compared with EOQ policy	-17%	-23%	Learning did not improve profit
No of subjects achieved higher profit than EOQ policy	0	1	A subject learnt the concept and applied it.
Average numbers of unit short	39.98	32.56	Unit shortage is greater before NV training
Average numbers of unit over	35.98	51.35	Unit overage is greater after NV training

Table 20 (Continued)

Analysis	Prior to Training	Post Training	Comments
Adjustment: No change from previous order quantity	45.90%	43.40%	Consistent for before and after learning
Adjustment: Change order quantity toward previous demand	36.70%	39.80%	Consistent for before and after learning
Adjustment: Change order quantity away from previous demand	17.40%	16.80%	Consistent for before and after learning
Correlation between direction of change in order and difference between previous demand and previous order	Significant at 95%	Not significant (n.s.)	Before learning: 45.8% of the subjects showed significant correlation. After learning: 45.5%.
C-W+	155.44	177.98	Subjects consistently ordered too low for high profit item
C+W+	114.84	140.86	Subjects consistently ordered too high for low profit item
C+W-	88.73	129.92	Subjects consistently ordered too high for low profit item
C-W-	160.68	179.13	Subjects consistently ordered too low for high profit item
Standard Deviation of OQ	51.08	56.62	Consistently below the standard deviation of random demand (75.0).
$q_{PRA}* < q_{WRA}*$	Significant	Significant	Wealthier decision-makers ordered more.
$H_0 : p_e \leq 0$ $H_1 : p_e > 0$	0.184	0.401	Subjects relied significantly more on expected demand after training.
$H_0 : p_u \leq 0$ $H_1 : p_u > 0$	0.173	0.114	Subjects consistently anchored their decisions on utility order policy
$H_0 : p_d \leq 0$ $H_1 : p_d > 0$	0.044	0.009(n.s.)	The magnitude of demand chasing heuristic is relatively small
$H_0 : p_q \leq 0$ $H_1 : p_q > 0$	0.558	0.504	Subjects consistently anchored their decision mostly on previous order quantity

5.2 Experiment II: Effects of Item Profit Margin and Item Salvage Value

This Section presents empirical results of statistical analysis of the effects of item profit margin and non-zero item salvage value on newsvendor decision-making. This empirical study extends current empirical studies of the NV problem which have only tested the significance of item profit margin (Schweitzer and Cachon, 2000, Bolton and Katok, 2004). Student subjects from the School of Industrial and Systems Engineering at Georgia Tech were recruited to participate in this experiment. These students were enrolled in a course that would teach the concept and the formulation of the classical newsvendor problem. This group of students participated in this experiment before and after they learned the concept and formula of the NV problem.

5.2.1 Experiment II Design and Protocols

This 2^2 factorial design experiment has 4 treatment levels (Table 21). The item profit margin, defined as $\frac{p-c}{p-s}$ has 2 levels, the low profit margin (0.25) and the high profit margin (0.75). The item salvage value has 2 levels, the zero salvage value and the non-zero salvage value.

Table 21: Newsvendor Experiment II Treatment Levels Summary

Treatment 1 (C-S-)	Treatment 2 (C-S+)	Treatment 3 (C+S-)	Treatment 4 (C+S+)
Revenue: \$12 Cost: \$3 Salvage: \$0	Revenue: \$12 Cost: \$9 Salvage: \$8	Revenue: \$12 Cost: \$9 Salvage: \$0	Revenue: \$12 Cost: \$11 Salvage: \$8

Each treatment level was replicated 4 times. The experiment run order was randomized to eliminate any time dependency effects. This experiment utilized the same procedure as the NV Experiment I discussed in previous Section. This experiment was conducted before subjects received NV training in June, 2004 and after subjects received NV training in July 2004. 28 subjects completed this experiment before learning NV problem and 27 subjects completed this experiment after learning NV problem.

5.2.2 Experiment II Results and Analysis (Before Learning NV)

This Section compiles the statistical analyses on the data collected from this experiment into two major categories:

1. Factorial design experiment analyses.
2. Analyses of mean and variance of NV order quantity.

5.2.2.1 Factorial design experiment analyses

This factorial experiment analysis investigates the significance of the nonzero salvage value term and the item profit margin term on newsvendor order quantities before subjects receive formal training on NV problem. The average order quantity of all subjects from each treatment level replication was compiled in such a way that each treatment condition has 4 data points. Figure 33 presents the normal probability plot of residuals. This plot appears satisfactory, so we have no reason to suspect problems with the validity of our assumptions on the underlying distribution.

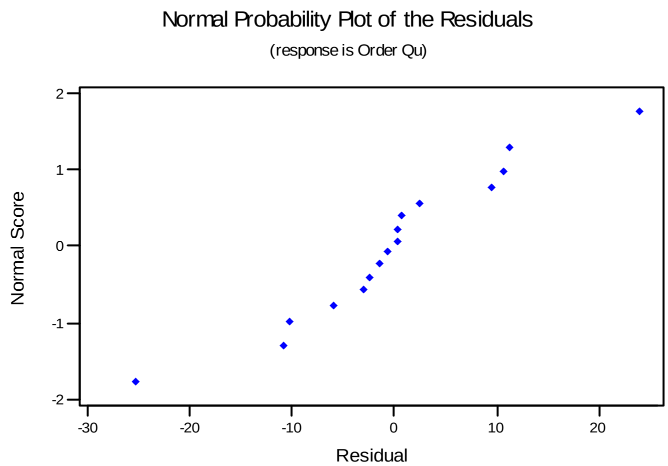

Figure 33: Exp. II (Before Learning NV) Normal Probability Plot of the Residuals

Average order quantity

This factorial design experiment is set up and analyzed in the MINITAB version 14 software. Figure 34 displays the effect estimates, the regression coefficients, and the sum of squares for each main effect and interaction. For these subjects, this statistical analysis indicates only the item profit margin to significantly affect newsvendor order quantity. The estimated effect for the cost term is -68.25 which means decision-makers ordered less under higher cost conditions than under lower cost conditions. The nonzero salvage value and its interaction with the item profit margin terms are not significant.

```
Estimated Effects and Coefficients for Order (coded units)

Term                   Effect      Coef     SE Coef        T      P
Constant                         159.45       3.098    51.48  0.000
Cost                   -68.25    -34.12       3.098   -11.02  0.000
Cost-Sal                 1.34      0.67       3.098     0.22  0.832
Cost*Cost-Sal            6.01      3.01       3.098     0.97  0.351

Analysis of Variance for Order (coded units)

Source                 DF      Seq SS     Adj SS     Adj MS      F       P
Main Effects            2     18637.0    18637.0     9318.5  60.70   0.000
2-Way Interactions      1       144.6      144.6      144.6   0.94   0.351
Residual Error         12      1842.2     1842.2      153.5
  Pure Error           12      1842.2     1842.2      153.5
Total                  15     20623.9
```

Figure 34: Exp. II (Before Learning NV) Factorial Design Analysis and ANOVA Summary

Individual order quantity

This section investigates the percentage of NV subjects whose decision-making is influenced by either the item cost term or the nonzero salvage value term. The analysis results (Table 22) show that 75% of the subjects were influenced by at least one of the main factors. The item profit margin and the nonzero salvage value factors affected the decision making of 68% and 14% of the subjects respectively.

Table 22: Exp. II (Before Learning NV) Summary of Percentage of Participants with Significant Factors

Factor	Significant	Not Significant
Profit Margin	68%	32%
Cost-Salvage Values	14%	86%
Either One	75%	25%

From the factorial design analysis results, we can conclude that the introduction of a salvage value term in the NV problem does not significantly influence the NV decision-making.

5.2.2.2 Descriptive statistics of NV order quantity

This Section discusses the existence of human decision bias as inferred from the subjects' order quantities. Figure 35 summarizes descriptive statistics and the confidence intervals of the average order quantity in various treatment conditions of this experiment. These 95% confidence intervals show that the average order quantities of subjects to deviate significantly from mean and from profit maximizing order quantities. The standard deviations of average order quantities in all treatment condition are smaller than the standard deviation of the consumer demand (75.0). The statistical analysis on the aggregate order quantity confirms human decision bias to exist in NV problem with and without item salvage value.

Variable	N	Mean	StDev	SE Mean
C-S-	112	195.91	47.30	4.47
C-S+	112	191.24	66.05	6.24
C+S-	112	121.65	47.55	4.49
C+S+	112	129.01	61.83	5.84

Variable	95.0% CI
C-S-	(187.05, 204.77)
C-S+	(178.87, 203.61)
C+S-	(112.75, 130.55)
C+S+	(117.43, 140.59)

Figure 35: Exp. II (Before Learning NV) Descriptive Statistics and Confidence Intervals of Average Order Quantity

5.2.3 Experiment II Results and Analysis (Post Learning NV)

This section compiles the statistical analyses on the data collected from experiment II subjects who have received NV training. The classroom exercise results indicated the student subjects understood the methods to solve the NV problem. We again present the statistical analyses of the data collected from this experiment in two major categories:

1. Factorial design experiment analyses.
2. Analyses of mean and variance of NV order quantity.

5.2.3.1 Factorial design experiment analyses

This factorial experiment analysis investigates the significance of the nonzero salvage value term and the item profit margin term on newsvendor order quantities after subjects receive formal training on NV problem. The average order quantity of all subjects from each treatment level replication was compiled in such a way that each treatment condition has 4 data points. Figure 36 presents the normal probability plot of residuals. This plot appears satisfactory, so we have no reason to suspect problems with the validity of our assumptions on the underlying distribution.

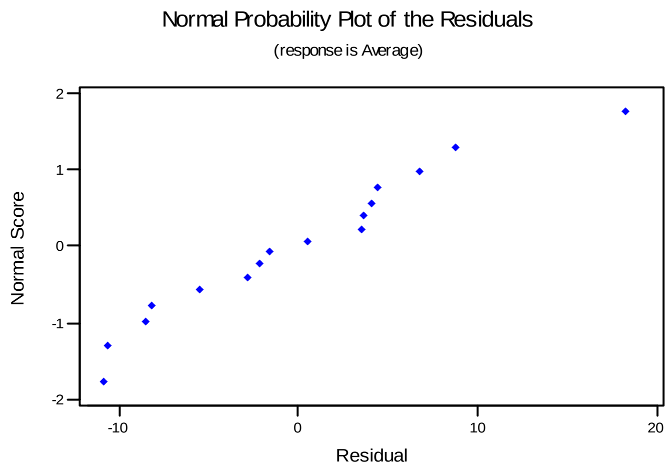

Figure 36: Exp. II (Post Learning NV) Normal Probability Plot of the Residuals

Average order quantity

This factorial design experiment is set up and analyzed in the MINITAB version 14 software. Figure 37 displays the effect estimates, the regression coefficients, and the sum of squares for each main effect and interaction. For these subjects, this statistical analysis indicates only the item profit margin to significantly affect newsvendor order quantity. The estimated effects for the cost term is -71.73 which means decision-makers ordered less under higher cost conditions than under lower cost conditions. The nonzero salvage value and its interaction with the item profit margin terms are not significant.

```
Estimated Effects and Coefficients for Average (coded units)

Term                    Effect      Coef     SE Coef        T      P
Constant                          148.80       2.211    67.29  0.000
Cost                    -71.73    -35.87       2.211   -16.22  0.000
Cost-Sal                 -3.85     -1.93       2.211    -0.87  0.401
Cost*Cost-Sal             7.34      3.67       2.211     1.66  0.123

Analysis of Variance for Average (coded units)

Source                  DF      Seq SS     Adj SS      Adj MS       F      P
Main Effects             2     20641.0    20641.0     10320.5 131.90  0.000
2-Way Interactions       1       215.7      215.7       215.7   2.76  0.123
Residual Error          12       939.0      939.0        78.2
  Pure Error            12       939.0      939.0        78.2
Total                   15     21795.6
```

Figure 37: Exp. II (Post Learning NV) Factorial Design Analysis and ANOVA Summary

Individual order quantity

This Section investigates the percentage of NV subjects whose decision-making is influenced by either the item cost term or the nonzero salvage value term. The analysis results (Table 23) show that 70% of the subjects were influenced by at least one of the main factors. The item profit margin and the nonzero salvage value factors affected the decision making of 67% and 22% of the subjects respectively.

Table 23: Exp. II (Post Learning NV) Summary of Percentage of Participants with Significant Factors

Factor	Significant	Not Significant
Profit Margin	67%	33%
Cost-Salvage Values	22%	78%
Either One	70%	30%

From the factorial design analysis results, we can conclude that the introduction of a salvage value term in the NV problem does not significantly influence the NV decision-making.

5.2.3.2 Descriptive statistics of NV order quantity

This Section discusses the existence of human decision bias as inferred from the subjects' order quantities. Figure 38 summarizes descriptive statistics and the confidence intervals of the average order quantity in various treatment conditions of this experiment. These 95% confidence intervals show that the average order quantities of subjects to deviate significantly from mean and from profit maximizing order quantities. The standard deviations of average order quantities in all treatment condition are smaller than the standard deviation of the consumer demand (75.0). The statistical analysis on the aggregate order quantity confirms human decision bias to exist in NV problem with and without item salvage value.

Variable	N	Mean	StDev	SE Mean
C-S-	108	190.26	48.45	4.66
C-S+	108	179.06	65.10	6.26
C+S-	108	111.19	52.08	5.01
C+S+	108	114.68	61.43	5.91

Variable	95.0% CI
C-S-	(181.02, 199.50)
C-S+	(166.65, 191.48)
C+S-	(101.25, 121.12)
C+S+	(102.96, 126.39)

Figure 38: Exp. II (Post Learning NV) Descriptive Statistics and Confidence Intervals of Average Order Quantity

5.2.4 Experiment II Conclusion

This section discusses the major findings from Experiment II before and after student subjects receive formal training on NV problem.

The most surprising result is that learning about the newsvendor problem a short time prior to the experiment did not remove the newsvendor decision bias as indicated in Figure 39. A slight improvement in NV decision-making after receiving NV training is found under the low profit conditions (C+S+, C+S-) where the average order quantities are closer to the EOQ (75).

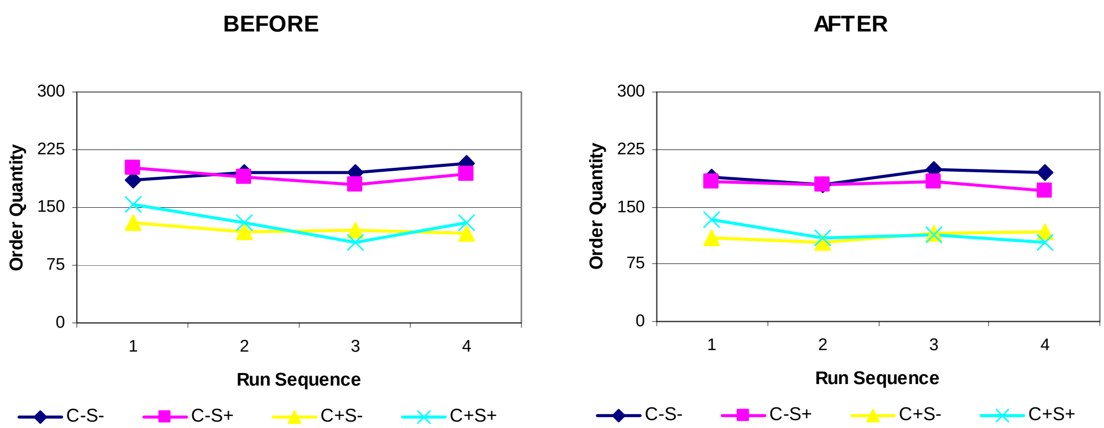

Figure 39: Exp. II Average Order Quantity vs. Run Sequence

Table 25 presents a summary of major results of experiment II before and after subjects received NV training. The newsvendor decision-makers consistently ordered too much under low profit margin condition and ordered too little under high profit margin condition. Profit margin factor was the only main factor influencing newsvendor decision-makers across all treatment conditions. Introduction of salvage value did not significantly affect newsvendor's decision-making.

An implication to this result is that the seller has power over the retailer under the high profit margin condition by his ability to choose the most favorable 'buyback' contract. Consider a NV item of profit margin, *m* which gives an optimal order quantity, q^*. Due to the inefficiency of supplier-retailer wholesale pricing contract, there is not a wholesale price to which the retailer, as the price-taker, will order at q^*. A "Buyback" contract is introduced to create a profit margin for the retailers equal to the item profit margin, *m* (Pasternack, 1985). The cost structure in the high profit margin condition (p=12, c=3, s=0) has an item profit margin of 0.75 and an optimal stocking level, q^* of 225. It is easy to see that any wholesale price between \$3 and \$12 will result in a retailer's optimal order quantity to be less than q^*. However, the supplier can introduce buyback contracts as shown in Table 24 where risk neutral retailers will order at q^*.

Table 24: High Profit Margin Buyback Contracts

Contract	Wholesale Price	Buyback Price	Retail Price
1	9	8	$12
2	7.5	6	$12
3	3	0	$12

Given the situation as depicted above, it is most beneficial for the supplier to choose option 1 because option 1 has the highest expected profit for the supplier and the optimal order quantity of the retailers is always q^* regardless of supplier's contract offer. Figure 40 shows that under option 1, supplier has higher expected profit or share a bigger proportion of total supply chain profit than the retailers. A fair contract which splits the total supply chain profit will be option 2. Since the retailer may not know the actual cost of the item, the supplier can offer any contract to the retailer. The supplier's power to choose any buyback price contract and the insignificant change in the retailer's order quantity with respect to the item salvage value (buyback value) term, as shown by the empirical evidence, result in a seller dominant market under the high profit margin condition.

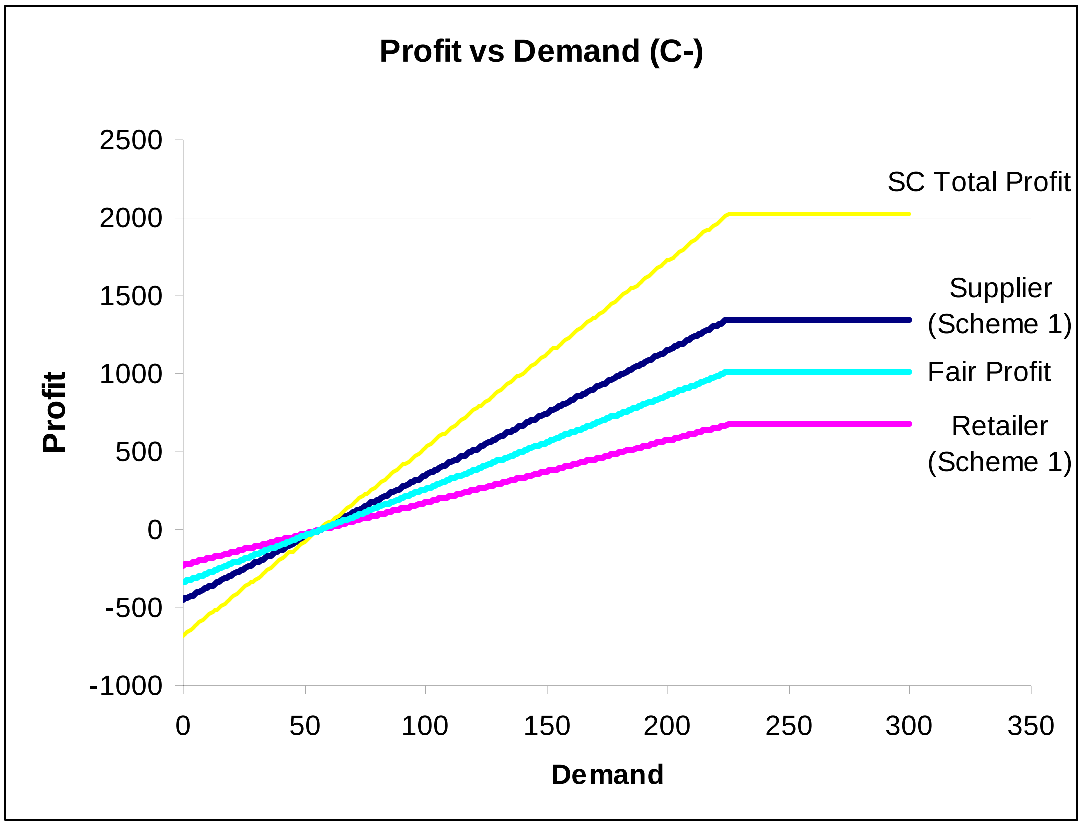

Figure 40: Profit against Demand of Various Buyback Contracts

The empirical evidence here also disputes the theoretical inefficiency of the supplier-retailer wholesale contract in the low item profit margin condition. Due to human decision bias, retailers' order quantity is higher than q^* for low profit margin. Setting a supplier-retailer wholesale contract with a wholesale price, w between c and p may prove to be just the remedy to decrease retailer's order quantity to adhere closer to

q^*. Therefore, the decrease in the item profit margin for the retailer with HDB results in a reduction of the too high order quantity.

Table 25: Exp. II Result Summary

Analysis	Before Learning NV	After Learning NV
Number of participants	28	27
Normality test	yes	yes
Profit margin factor	Significant at 95%	Significant at 95%
Salvage value factor	Not significant	Not significant
Interaction between main factors	Not significant	Not significant
Initial order quantity	< 150 for low profit item, > 150 for high profit item	< 150 for low profit item, > 150 for high profit item
% of subjects with significant profit margin factor	67.86%	66.67%
% of subjects with significant salvage value factor	14.29%	22.22%
Trend of order quantity over time	Not significant	Not significant
Deviation from mean	Significant at 95%	Significant at 95%
Deviation from profit maximizing EOQ	Significant at 95%	Significant at 95%
Average Order Quantity (C-S-)	195.91	190.26
Average Order Quantity (C-S+)	191.24	179.06
Average Order Quantity (C+S-)	121.65	111.19
Average Order Quantity (C+S+)	129.01	114.68
Standard Deviation of OQ	65.77	67.47

CHAPTER 6: MULTI-ECHELON NEWSVENDOR SUPPLY CHAIN EXPERIMENTS

This Chapter investigates newsvendor decision-making in a multi-echelon supply chain (SC) system. The effects of NV initial wealth and item profit margin on the order quantity of NV subjects under tight and loose supplier-retailer relationship are studied in a NV supply chain game. Empirical evidence will show (1) information sharing between supplier and retailer improves NV decision-making for the suppliers but not for the retailers, (2) the human decision bias exists in this multi-echelon NV supply chain and accounts for more than 25% of loss of total supply chain profit, (3) a reversed "Bullwhip Effect" exists in NV supply chain, and (4) the suppliers rely on different procurement policies of the HDB model under different relationships with the retailers.

6.1 Empirical Studies of Supply Chain: A Literature Review

This section reviews related empirical research in supply chain systems. A key tradeoff in supply chain systems is keeping inventory costs low and customer service levels high. The upstream amplification of inventory variability in the supply chain, known as the bullwhip effect, is a major area of opportunity to reduce supply chain inventory costs, which account for about 20-40% of the cost of the product. It is not surprising that a significant amount of research, both theoretical and empirical, in supply chain inventory management investigates sources of the bullwhip effects and ways to reduce it (Disney and Towill, 2003).

Empirical methodologies on supply chain systems can be divided into two major categories. The first utilizes computer simulation of SC systems such as a bullwhip effect simulator system developed to study how information sharing can improve supply chain performance (Gangopadhyay and Huang, 2002). The second methodology involves human subjects playing different roles in a SC system. The “Beer Distribution Game” is the most commonly used role-playing simulation of a supply chain system in many management courses as well as industry settings. Participants in this game play an assortment of inventory managerial roles in the SC with the objective of optimizing the tradeoff between holding cost and backlog cost. Sterman (1989) was first to use this role playing simulation of SC system to analyze the “bullwhip effect” and found the human behavioral cause of this upstream oscillation and amplification of customer demand in the SC system. The investigator concludes that subjects are biased towards incoming demand and often fail to account for pipeline inventory. Croson and Donohue (2002), and Banerji et al. (2004) extend Sterman’s result to investigate effects of different parameters in the beer games such as lead time, number of echelons, different demand characteristics, and information sharing on SC performance.

We developed and ran a newsvendor supply chain game which differed from the “Beer Distribution Game” in two ways. First, while the “Beer Distribution Game” allows participant to hold inventory from one period to another for a certain holding cost, the newsvendor SC game does not have a holding cost. Perishable items such as fresh produce, newspapers, or fashion goods are salvaged in the end of the selling period. Second, the objective of the newsvendor supply chain game is different from the objective of the “Beer Distribution Game”. The newsvendor SC game maximizes total profit while the non perishable SC game minimizes total cost.

This newsvendor SC game is set up to study the effects of item profit margin, NV initial wealth, and the relationship between supplier and retailer on the performance of the supply chain system. The item profit margin and the NV initial wealth are proven both analytically and empirically to affect the order quantity in the single newsvendor setting. The newsvendor SC game extends the empirical studies of NV problem to a multi-echelon newsvendors setting.

Information sharing and cooperation between different players in the SC systems are some ways of improving the performance of the SC. The cooperation between multiple retailers of newsvendor type products with transshipments will theoretically increase the expected profit for the retailers in the cooperation pool (Fransoo et al., 2005). The investigators, like many others, rely on the assumption that the newsvendor will order the optimal order quantity of the classic NV problem.

6.2 Two-Echelon Newsvendor Supply Chain Game

This Section discusses the impact of human decision bias on a 2-echelon NV supply chain game. For brevity, we omit the literature review of game theory in supply chain management which is found in (Cachon and Netessine).

We model a 2-echelon NV supply chain game as a Stackelberg (1934) game which is played by 2 players, a *leader* who initiates the game and *a follower* who responses. This 2-echelon NV game defines the NV supplier as the *leader* and the NV retailer as the *follower*. The *leader* in this game does not know the consumer demand completely (he may know the demand is uniformly distributed between 0 and a fixed maximum number) and has to wait for signals from the *follower* for the missing information.

The standard notation of game theory adapted from (Cachon and Netessine) consists of (i) *players* indexed by i=1,..,n, (ii) *strategies* denoted by x_i, i=1,..,n available to all players and (iii) *payoff* π_i, i=1,..,n received by each player.

Definition 1: *The best response function of player i given the strategies of other player,* x_{-i}^* *is defined as the strategy* x_i^* *that maximizes player i's payoff* $\pi_i(x_i, x_{-i})$*:*

$$x_i^*(x_{-i}) = \arg\max_{x_i} \pi_i(x_i, x_{-i}).$$

Definition 2: *An outcome* $(x_1^*, x_2^*, \ldots, x_n^*)$ *is a Nash equilibrium of the game if* x_i^* *is the best response to* x_{-i}^* *for all i=1,..,n.*

We will conduct this game for 2 periods with a supplier as the *player 1* (P_1) and a retailer as the *player 2* (P_2).

Period 1:

P_1 sets retail price, p and wholesale price, c and reserves capacity x_1.

Period 2:

P_2 responses with an order quantity, x_2 according to his preferences.

Case 1: P_1 and P_2 are risk-neutral

We follow a game-theoretical approach and solve the problem with backward induction. We begin by first solving for the response function of the follower (retailer), P_2, given that he has observed the leader, P_1's decision. Then, we solve the response of the supplier given that he knows how the retailer will react to his decision.

Retailer's response function

Let $\pi_2(q,D) = p\min(q,D) - cq$ be the payoff function for the retailer, P_2. The expected payoff function for P_2 is given by:

$$E[\pi_2(q,D)] = (1-F(q))(p-c)q + \int_0^q f(x)\pi_2(q,x)dx \tag{1}$$

The risk-neutral retailer here must choose q that will maximize (1) such that

$$q^* \in \arg\max_q E[\pi_2(q,D)]$$

can be obtained by the first order condition:

$$\frac{\partial E[\pi_2(q,D)]}{\partial q} = 0$$

From the classic NV solution we obtain

$$x_2 = q^* = F^{-1}\left(\frac{p-c}{p}\right)$$

Supplier's response function

Let D_R be the demand from the retailer with $g(x)$ and $G(x)$ as its p.d.f. and c.d.f., respectively. Let c_s be the unit production cost and $\pi_1(q,D_R) = c\min(q,D_R) - c_s q$ be the payoff function for P_1. The expected payoff function for P_1 is given by:

$$E[\pi_1(q,D)] = (1-G(q))(c-c_s)q + \int_0^q g(x)\pi_1(q,x)dx \tag{2}$$

The risk-neutral supplier here must choose q that will maximize (2) such that

$$q^* \in \arg\max_q E[\pi_1(q,D)]$$

From the classic NV solution we obtain

$$x_1 = G^{-1}\left(\frac{c-c_s}{c}\right)$$

Since the probability function of the D_R is such that $P(D_R = x_2) = 1$ and $P(D_R \neq x_2) = 0$, so it follows that $x_1 = q^* = F^{-1}\left(\frac{p-c}{p}\right)$.

The outcome of this game is a Nash equilibrium because no player can benefit from deviation of their respective strategies.

Case 2: P_1 is risk-neutral and P_2 has HDB

We again follow the game-theoretical approach to solve this problem with backward induction. We begin by first solving for the response function of P_2, given that he has observed P_1's decision. Then, we solve the response of the P_1 given that he knows how the retailer will react to his decision.

Retailer's response function

Suppose retailer exhibits human decision bias by being risk-seeking when item profit margin is low and being risk-averse when item profit margin is high. Let $b \in [0,1]$ be a bias parameter such that

$$x_2 = (1-b)F^{-1}\left(\frac{p-c}{p}\right) + b\overline{D},$$

where $\overline{D}$ is the expected demand.

The payoff function for retailer is $\pi_2(x_2, D) = p\min(x_2, D) - cx_2$ and the expected payoff is given by:

$$E[\pi_2(x_2, D)] = (1 - F(x_2))(p-c)x_2 + \int_0^{x_2} f(x)\pi_2(x_2, x)dx$$

Supplier's response function

Let D_R be the demand from the retailer with *g(x)* and *G(x)* as its p.d.f. and c.d.f., respectively. Let c_s be the unit production cost and $\pi_1(q, D_R) = c\min(q, D_R) - c_s q$ be the payoff function for P_1. The expected payoff function for P_1 is given by (2):

The risk-neutral supplier here must choose q that will maximize (2) such that

$$q^* \in \arg\max_q E[\pi_1(q, D)]$$

From the classic NV solution we obtain

$$x_1 = G^{-1}\left(\frac{c - c_s}{c}\right)$$

Since the probability function of the D_R is such that $P(D_R = x_2) = 1$ and $P(D_R \neq x_2) = 0$, so it follows that $x_1 = q^* = (1-b)F^{-1}\left(\frac{p-c}{p}\right) + b\overline{D}$.

The outcome of this game is also a Nash equilibrium because no player can benefit from deviation of their respective strategies. However, the total channel payoff in this case is less than the risk-neutral case.

Hypothesis 6.1: HDB Newsvendor SC Total Payoff Hypothesis

$$H_o : \sum_{i=1}^{n} \pi_i^{HDB} \geq \sum_{i=1}^{n} \pi_i^{EOQ}$$
$$H_1 : \sum_{i=1}^{n} \pi_i^{HDB} < \sum_{i=1}^{n} \pi_i^{EOQ}$$

The null Hypothesis 6.1 states that the total payoff of all agents in a NV game of HDB subjects is greater or equal to the NV game of subjects following EOQ policy. The alternative hypothesis states that the total payoff of all agents in a NV game of HDB subjects is less than the NV game of subjects following EOQ policy. This hypothesis will be tested in the NV supply chain experiment in Section 6.5.2.

6.3 Multi-Echelon Newsvendor HDB Model

This Section presents a natural extension of the HDB model in the single NV setting to a multi-echelon NV setting. Hypotheses of this MEHDB will be constructed and tested in the multi-echelon NV experiment in Section 6.5.4.

Consider a 2-echelon NV supply chain of *n* suppliers and *n* retailers. Suppliers agree on a fixed wholesale price, c_r for the retailers, and receives an order quantity from retailer *i*, q_i. Retailers set a fixed retail price, *p* which generates a consumer demand distribution, *D*. Assuming zero salvage value, the optimal order quantity for the retailers is $q^* = F^{-1}\left(\frac{p - c_r}{p}\right)$. The supplier's optimal order quantity will also be q^*. Indeed, the total supply chain profit is maximized by these decisions.

Let us assume that the retailers have different human decision biases and their order quantities, q^{Ri} has mean, m_i and variance, v_i. For simplicity, let us rank retailers in an increasing manner such that $m_i > m_j$ for $i>j$. Two conditions of the supplier and retailer relationship are illustrated in Figure 41. The first condition is a tight relationship (R+) which is defined as a relationship of frequent contact and information exchange between the retailer and supplier. Under R+, each supplier receives order from the same retailer in each ordering period. The second condition is a loose relationship (R-) which is defined as a relationship of infrequent contact and limited information exchange between the retailer and supplier. Under R-, each supplier will receive orders from a random retailer in each ordering period.

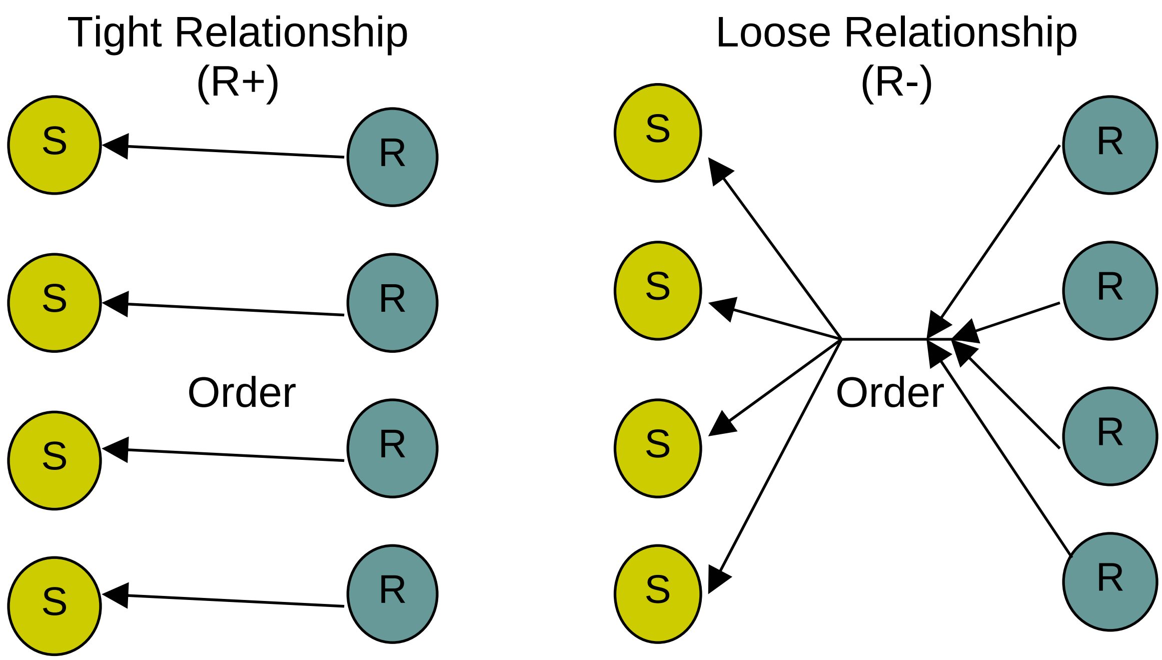

Figure 41: Exp. III Relationship between Suppliers and Retailers

Under different relationship conditions and human decision bias, we propose the MEHDB model for the supplier NV as (1):

$$q_t^S = p_e^S \overline{D} + p_u^S q^* + p_d^S q_{t-1}^{R_i} + p_q^S q_{t-1}^S \tag{1}$$

where

$$q_{t-1}^{R_i} = p_e^{R_i} \overline{D} + p_u^{R_i} q^* + p_d^{R_i} D_{t-2} + p_q^{R_i} q_{t-2}^{R_i} \tag{2}$$

q_t^S : The supplier's order quantity at time t

p_e^S : Weight of supplier's reliance on expected demand policy

p_u^S : Weight of supplier's reliance on EOQ

p_d^S : Weight of supplier's reliance on chasing retailer's demand policy

p_q^S : Weight of supplier's reliance on q_{t-1}

q_t^{Ri} : Retailer i's order quantity at time t

p_e^{Ri} : Weight of retailer i's reliance on expected demand policy

p_u^{Ri} : Weight of retailer i's reliance on EOQ

p_d^{Ri} : Weight of retailer i's reliance on chasing consumer's demand policy

p_q^{Ri} : Weight of retailer i's reliance on q_{t-1}

$\overline{D}$: Expected value of consumer demand

q^*: EOQ of a risk neutral NV, $q^* = F^{-1}\left(\frac{p-c}{p-s}\right)$

D_t : Realization of consumer demand at time t.

Notice that the MEHDB model for the retailer is the HDB model proposed in Chapter 4 because the supply chain game condition for the retailers is set up the same way as the single NV setting. The MEHDB model for the NV supplier includes the factors affecting downstream retailer's decision as described in (2). Obviously, this model can extend to a more general multi-echelon NV decision bias model, where the upstream agent's decision is affected by all downstream agents' decisions. For example, in this 2-echelon case, the supplier's order quantity is affected by the consumer's demand as shown by substituting (2) into (1), which gives

$$q_t^S = p_e^S \overline{D} + p_u^S q^* + p_d^S (p_e^{R_i} \overline{D} + p_u^{R_i} q^* + p_d^{R_i} D_{t-2} + p_q^{R_i} q_{t-2}^{R_i}) + p_q^S q_{t-1}^S \quad (3)$$

The demand distribution faced by the suppliers varies under different relationship conditions due to human decision bias. In the tight relationship (R+) case, where a supplier S is paired with a retailer throughout the SC game, the index i for the retailers in Equation (3) is a constant because supplier S only deals with one retailer. Therefore, the

(R+) supplier faces the demand distribution (m_i, v_i) with probability 1 throughout the game. In the loose relationship (R-) case, where different retailers order from a supplier, the supplier S faces different demand distributions (m_i, v_i) with probability b_i, which is the probability that retailer i is selected to order from supplier S.

Hypothesis 6.2: Chasing Retailer Demand Hypothesis

$$H_o : p_d^{S(R+)} \leq p_d^{S(R-)}$$
$$H_1 : p_d^{S(R+)} > p_d^{S(R-)}$$

Hypothesis 6.2 states that the R+ supplier will rely more on the retailer's order quantity than R- supplier. This hypothesis will be tested in the NV supply chain experiment in Section 6.5.5. The motivation to develop this hypothesis lies in the fact that supplier is more likely to face less demand variation in the R+ case than in the R- case. To illustrate this hypothesis analytically, we define:

$P_{t+1}(\alpha)$: Probability of $q_t^{Ri} - \alpha < q_{t+1}^{Ri} < q_t^{Ri} + \alpha$

α : The absolute deviation from previous order quantity

Assume v_i is constant and retailer's order quantity is normally distributed, then $P_{t+1}(\alpha)$ is constant for the R+ supplier. For the R- supplier there is $1/n$ chance that $P_{t+1}(\alpha)$ remain constant, and $(n\text{-}1)/n$ chance that it will change. Figure 42 illustrates a case of 2 retailers in the NV supply chain. Supplier faces demand from retailer 1, q^{R1} in tight relationship condition. Supplier faces demand from retailer 1 or 2 with equal probability under loose relationship condition. The shaded area in (a) shows the $P_{t+1}(\alpha)$ for R+ supplier and the shaded area in (b) shows the $P_{t+1}(\alpha)$ for R- supplier.

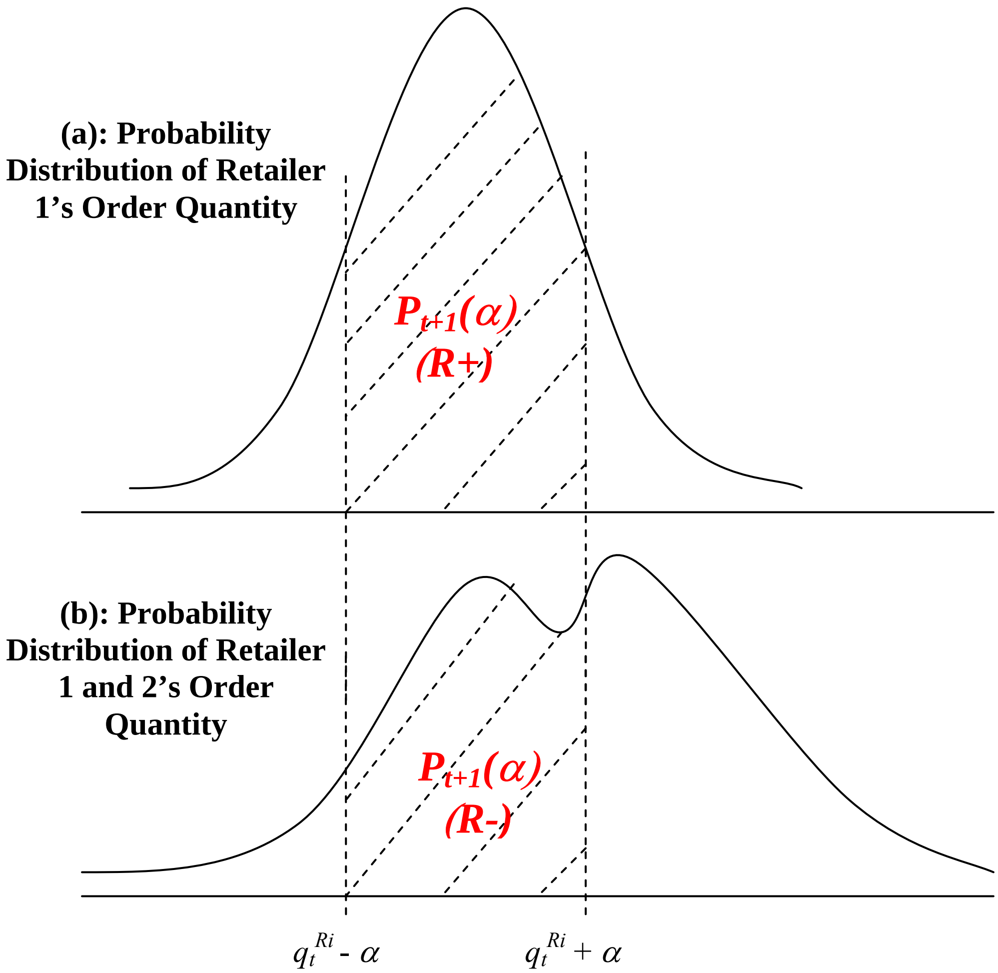

Figure 42: Comparison of Probability of Retailer's Demand under Various Relationship Conditions

Proposition 6.1: $P_{t+1}(\alpha)$ for R- < $P_{t+1}(\alpha)$ for R+.

Proof: Let $m_1 = m_2 - k$, where $k > 0$ is the difference between the average order quantities of retailer 1 and retailer 2. Let $\sigma = \sqrt{v_i}$ be the standard deviation of retailer's order quantity.

$P_{t+1}(\alpha)$ for R+ (shaded region in Figure 42a)

$$= \Phi\left(\frac{m_1 + \alpha - m_1}{\sigma}\right) - \Phi\left(\frac{m_1 - \alpha - m_1}{\sigma}\right)$$

$$= \Phi\left(\frac{\alpha}{\sigma}\right) + \Phi\left(\frac{\alpha}{\sigma}\right) - 1$$

$$> \frac{1}{2}\Phi\left(\frac{\alpha - k}{\sigma}\right) + \frac{1}{2}\Phi\left(\frac{\alpha + k}{\sigma}\right) + \Phi\left(\frac{\alpha}{\sigma}\right) - 1$$

$$= \frac{1}{2}\left(\Phi\left(\frac{\alpha - k}{\sigma}\right) + \Phi\left(\frac{\alpha + k}{\sigma}\right) - 1\right) + \Phi\left(\frac{\alpha}{\sigma}\right) - \frac{1}{2}$$

$$= \frac{1}{2}\left(\Phi\left(\frac{\alpha - k}{\sigma}\right) - \Phi\left(\frac{-\alpha - k}{\sigma}\right) - 1\right) + \frac{1}{2}\left(2\Phi\left(\frac{\alpha}{\sigma}\right) - 1\right)$$

$$= \frac{1}{2}\left(\Phi\left(\frac{m_1 + \alpha - m_1 - k}{\sigma}\right) - \Phi\left(\frac{m_1 - \alpha - m_1 - k}{\sigma}\right) - 1\right) + \frac{1}{2}\left(2\Phi\left(\frac{\alpha}{\sigma}\right) - 1\right)$$

$$= \frac{1}{2}\left(P\left(m_1 - \alpha < q^{R2} < m_1 + \alpha\right)\right) + \frac{1}{2}\left(P\left(m_1 - \alpha < q^{R1} < m_1 + \alpha\right)\right)$$

$= P_{t+1}(\alpha)$ for R- (shaded region in Figure 42b) □

This result implies that R+ suppliers will rely on chasing retailer demand heuristic more than the R- suppliers will.

6.4 Experiment III Design and Protocols

This Section presents the design and the protocols of this multi-echelon newsvendor experiment. The response variable is newsvendor's order quantity. The independent variables are (C) item profit margin, (W) NV initial wealth, and (R) relationship between supplier and retailer. This 2^3 factorial design experiment has 8 treatment conditions as shown in Table 26.

Table 26: Multi-Echelon Newsvendor Experiment III Treatment Levels Summary

Treatment 1 (R+C-W+)	Treatment 2 (R+C+W+)	Treatment 3 (R+C+W-)	Treatment 4 (R+C-W-)
Tight Relationship Wealth: \$10000 Revenue: \$12 Cost: \$3 Salvage: \$0	Tight Relationship Wealth: \$10000 Revenue: \$12 Cost: \$9 Salvage: \$0	Tight Relationship Wealth: \$500 Revenue: \$12 Cost: \$9 Salvage: \$0	Tight Relationship Wealth: \$500 Revenue: \$12 Cost: \$3 Salvage: \$0

Treatment 5 (R-C-W+)	Treatment 6 (R-C+W+)	Treatment 7 (R-C+W-)	Treatment 8 (R-C-W-)
Loose Relationship Wealth: \$10000 Revenue: \$12 Cost: \$3 Salvage: \$0	Loose Relationship Wealth: \$10000 Revenue: \$12 Cost: \$9 Salvage: \$0	Loose Relationship Wealth: \$500 Revenue: \$12 Cost: \$9 Salvage: \$0	Loose Relationship Wealth: \$500 Revenue: \$12 Cost: \$3 Salvage: \$0

The treatment conditions for the item profit margin and NV initial wealth are similar to the single NV experiment I in Chapter 5.2. There are 2 treatment conditions for the relationship term, the loose relationship (R-) and the tight relationship (R+) as illustrated in Figure 41. This experiment assumes that when a retailer orders more than what the supplier has in stock, the retailer will be able to get the unfilled order at cost from the supplier who will not make any profit. This assumption will limit the introduction of a shortage effect to the experiment and will allow us to better condition the effect of relationship term on NV decision-making.

Student subjects from the School of Industrial and Systems Engineering were recruited to participate in this experiment. This group of students participated in this experiment after they learned the concept and formula of the NV problem. Each treatment level was replicated 10 times. The subjects were told to order in such a way that would maximize their final wealth. The subjects were not informed the length of the experiment and were told that the experiments might end at any time. The actual demand was randomly generated during the experiment with the same random number generators previously used to provide past demand data for the subjects. Each subject was randomly selected to role play as either a supplier or a retailer. The suppliers and the retailers were separated into 2 rooms. Subjects either began with (R+C-W+) treatment condition or with (R-C-W+) treatment conditions.

Detailed procedure:

1. Each subject is provided with the consent form to participate in the experiment voluntarily and is informed that the subject can stop anytime during the experiment without penalty.

2. Upon receipt of the consent form, the principal investigator (PI) will provide each subject with past demand data.
3. The subject is then told about subject's current wealth level and the current cost structure of the item.
4. The PI informs the supplier subjects to place an order within a range.
5. The individual suppliers place order quantities.
6. The PI inform the retailer subjects to place orders within a range
7. The individual retailers place order quantities.
8. Retailers' order are conveyed to the suppliers by
    a. Mixing all orders together and randomly assigning one to each supplier for loose relationship conditions.
    b. Assigning the same retailer's order to the same supplier for tight relationship conditions.
9. The supplier is given time to review the demand data and current wealth.
10. The retailer is informed of the actual demand for that period and the resulting profit or loss.
11. The retailer is given time to review the demand data and current wealth.
12. Repeat step 3 until all subjects have completed the preset number of order periods.

A total of 35 subjects participated in the experiment as retailers, but only 23 of these retailer subjects completed the experiments. A total of 43 subjects participated in the experiment as suppliers, but only 25 of these supplier subjects completed the experiments. As a result, we report results from 23 retailer subjects and 25 supplier subjects. The experiment had been previously certified by the Institute Review Board (IRB) and was conducted at Georgia Institute of Technology in November, 2004.

6.5 Experiment III Results and Analyses

This Section presents the statistical analyses of the data collected from this multi-echelon NV supply chain experiment in five major categories:

1. Factorial design experiment analyses.
2. Analyses of NV supply chain performance.
3. Analyses of the "Bullwhip Effect" in NV supply chain.
4. MEHDB model fits.
5. Trends in NV's preferences of various procurement policies.

Empirical evidence will show (1) information sharing between supplier and retailer improves NV decision-making for the suppliers but not for the retailers, (2) the human decision bias exists in this multi-echelon NV supply chain and accounts for more than 25% of loss of total supply chain profit, (3) a reversed "Bullwhip Effect" exists in NV supply chain, and (4) the suppliers rely on different NV requisition policies of the MEHDB model under different relationship with the retailers.

6.5.1 Factorial Design Experiment Analyses

This section presents a 2^3 factorial experiment analysis to investigate the significance of the NV's initial wealth term, the item profit margin term, and the relationship between supplier and retailer term on newsvendor's decision-making. The response variables are supplier's average order quantity, the absolute deviation of supplier's order quantity from retailer's demand and retailer's average order quantity.

6.5.1.1 Supplier's average order quantity

The average order quantity of all supplier subjects from each treatment level replication was compiled in such a way that each of 8 treatment conditions has 10 data points. Figure 43 presents the normal probability plot of residuals, and the residuals appear to be normally distributed.

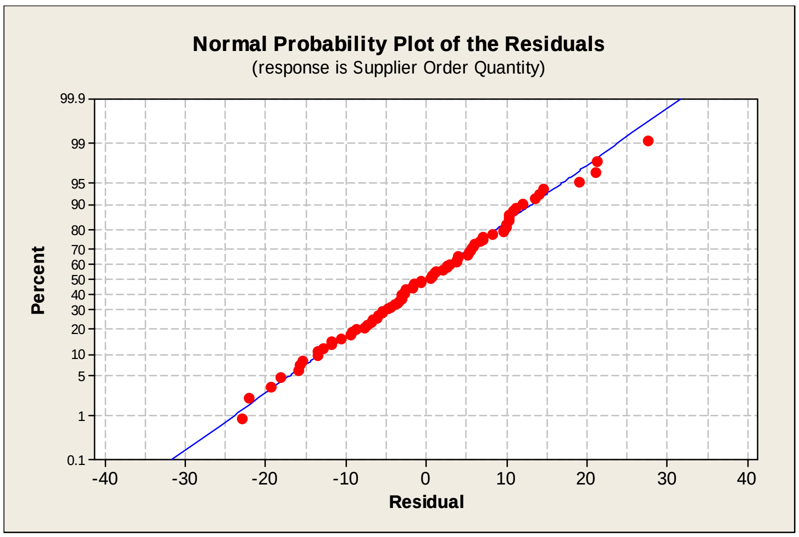

Figure 43: Exp. III Normal Probability Plot of the Residuals

Figure 44 displays the effect estimate, the regression coefficient, and the sum of squares for each main effect and interaction. For these subjects, this statistical analysis indicates all three main effects and the interaction between these factors to significantly affect newsvendor order quantity. The estimated effects for the aggregate data set shows the initial wealth term had positive effect of 18.3 which means higher order quantity is achieved at the high initial wealth level. The estimated effects for the profit margin term is 28.55 which means decision-makers ordered more under higher profit margin conditions than under lower profit margin conditions. The estimated effects for the relationship term is -19.83 which means decision-makers ordered more under loose relationship than under tight relationship conditions.

Estimated Effects and Coefficients for Supplier Order Quantity (coded units)

Term	Effect	Coef	SE Coef	T	P
Constant		132.708	1.199	110.67	0.000
Profit Margin	28.554	14.277	1.199	11.91	0.000
Wealth	18.304	9.152	1.199	7.63	0.000
Relationship	-19.838	-9.919	1.199	-8.27	0.000
Profit Margin*Wealth	-4.786	-2.393	1.199	-2.00	0.050
Profit Margin*Relationship	-10.376	-5.188	1.199	-4.33	0.000
Wealth*Relationship	-4.302	-2.151	1.199	-1.79	0.077
Profit Margin*Wealth*Relationship	6.164	3.082	1.199	2.57	0.012

S = 10.7251   R-Sq = 80.70%   R-Sq(adj) = 78.82%

Analysis of Variance for Supplier Order Quantity (coded units)

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Main Effects	3	30878.3	30878.3	10292.8	89.48	0.000
2-Way Interactions	3	2981.5	2981.5	993.8	8.64	0.000
3-Way Interactions	1	759.9	759.9	759.9	6.61	0.012
Residual Error	72	8282.0	8282.0	115.0		
Pure Error	72	8282.0	8282.0	115.0		
Total	79	42901.6				

Figure 44: Exp. III Factorial Design Analysis and ANOVA Summary

For these subjects, the interaction plot (Figure 45) shows that the two way interactions between these factors are generally mild except for interaction between the profit margin term and the relationship term. The interaction plot in the lower left corner of Figure 45 shows that the effect of relationship term is small when the profit margin is low and large when the profit margin is high. Therefore, we can conclude that initial wealth effect affects newsvendor decision-making most when item cost is high and that the item profit margin effect affects newsvendor decision-making regardless of the levels of newsvendor's initial wealth.

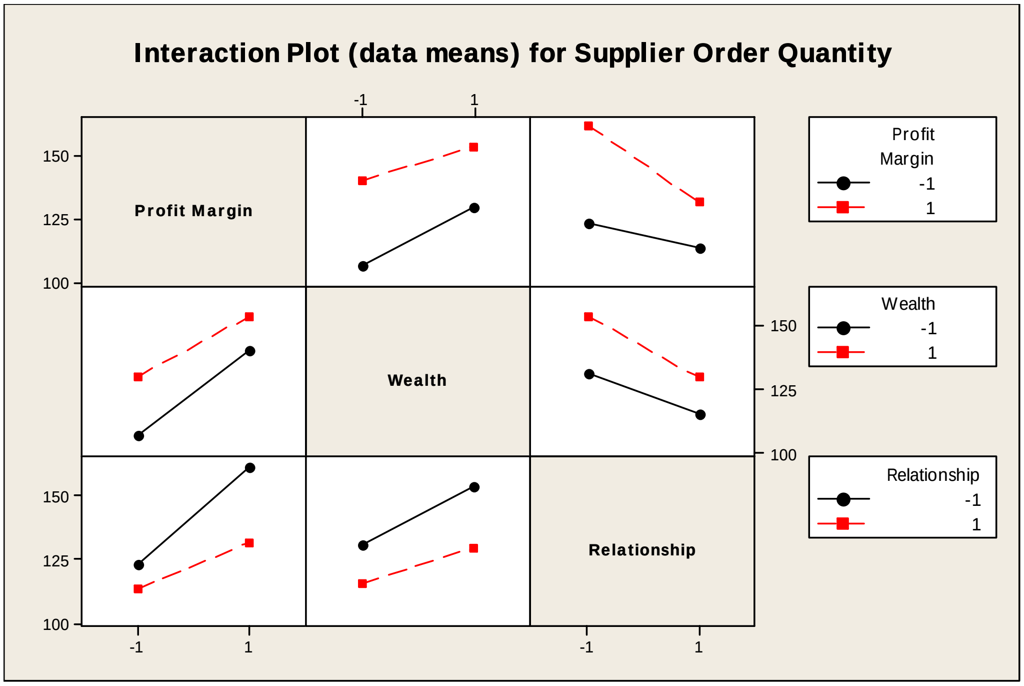

Figure 45: Exp. III Interaction Plots of Supplier's Order Quantity

The cube plot (Figure 46) is used to investigate any three-way interaction between these factors. The effect of the item profit margin term is consistent over any combination of relationship term and wealth term. The effect of the initial wealth term is significant over any combinations of the relationship and the item profit margin term. However, the effect of relationship term is very small in the low initial wealth low profit margin treatment combination and is very large in the low initial wealth high profit margin treatment combination. The average order quantities under the low initial wealth and the low profit margin are lowest among all treatment conditions and may have contributed to the relationship between retailer and supplier to be insignificant. This result suggests that the relationship between supplier and retailers term does not significantly affect newsvendor decision-making when the NV's initial wealth is low and the item profit margin is low.

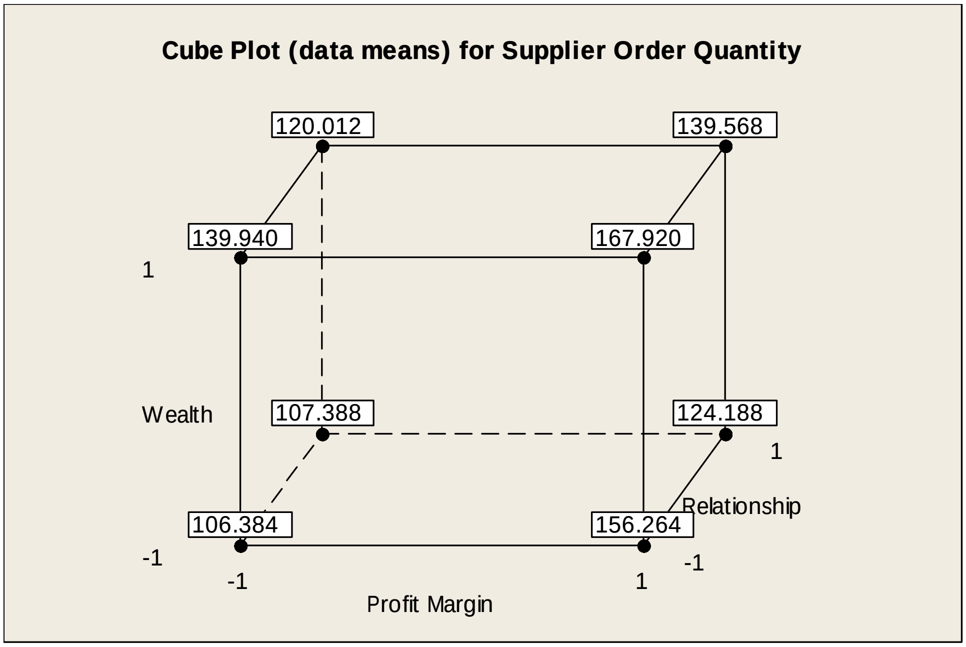

Figure 46: Exp. III Cube Plot for Supplier Order Quantity

6.5.1.2 Absolute deviation between the supplier's order quantity and demand

The following Section discusses the effect of the relationship term on the absolute deviation between supplier's order quantity and the demand from retailers in this multi-echelon NV experiment. The absolute deviation between the supplier's order quantity and the demand from the retailers is a better measure of supplier's decision-making because it accounts for the demand generated by the retailers. This analysis will reveal that a tighter relationship between supplier and retailer reduces the absolute deviation between the supplier's order quantity and the demand from retailers.

Table 27: Exp. III Estimated Effects and Coefficients for Absolute Deviation

Term	Effect	Coef	SE Coef	T	P
Constant		42.625	0.9302	45.82	0.000
Profit Margin	-3.980	-1.990	0.9302	-2.14	0.036
Wealth	4.968	2.484	0.9302	2.67	0.009
Relationship	-11.188	-5.594	0.9302	-6.01	0.000
Profit Margin*Wealth	6.906	3.453	0.9302	3.71	0.000
Profit Margin*Relationship	8.606	4.303	0.9302	4.63	0.000
Wealth*Relationship	5.646	2.823	0.9302	3.03	0.003
Profit Margin*Wealth*Relationship	-0.720	-0.360	0.9302	-0.39	0.700

Table 27 displays the effect estimate and the regression coefficient for each main effect and interaction term. This statistical analysis indicates all three main effects and the interaction between these factors to significantly affect the response variable. The estimated effects for the relationship term is -11.19, the largest among all effects, and that means the quality of supplier's order is better under tight relationship than loose relationship conditions.

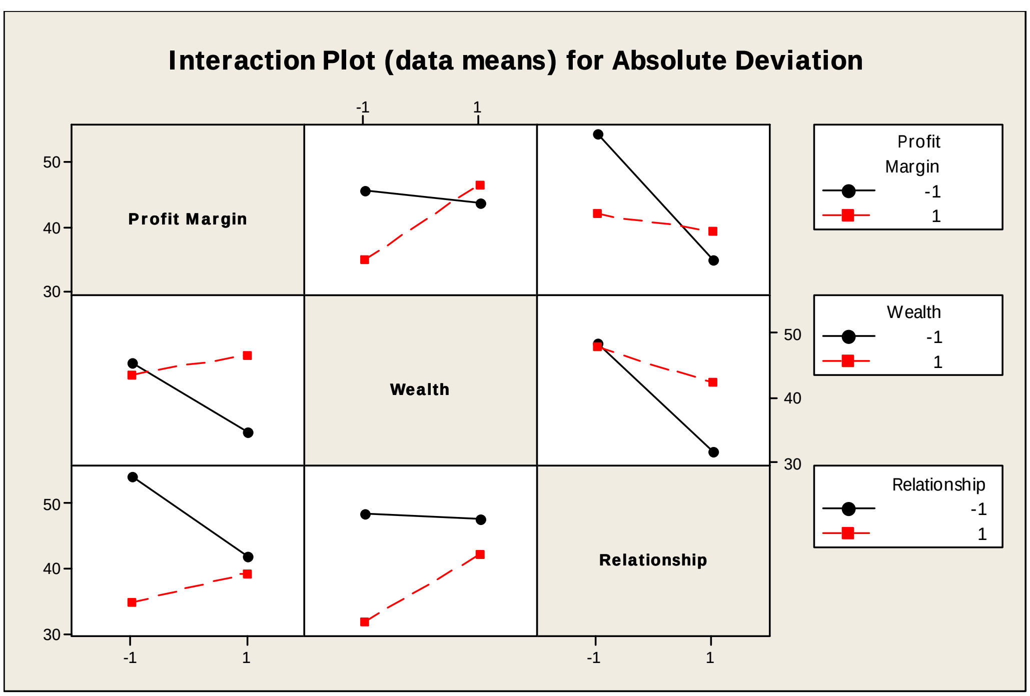

Figure 47: Exp. III Interaction Plots of Supplier's Order Quantity

The interaction plots (Figure 47) show many significant two-way interactions between these factors. The top row of interaction plots show that the effect of the profit margin term is large when the initial wealth term is low and the relationship term is loose. The second row of interaction plots show that the effect of the initial wealth term is large when the item profit margin term is high and the relationship term is tight. The last row of interaction plots show that the effect of the relationship term is large when the initial wealth term is low and the item profit margin is low. The interaction plots on the rightmost column indicate that the tight relationship condition consistently results in lower absolute deviation between supplier's order quantity and demand from retailers.

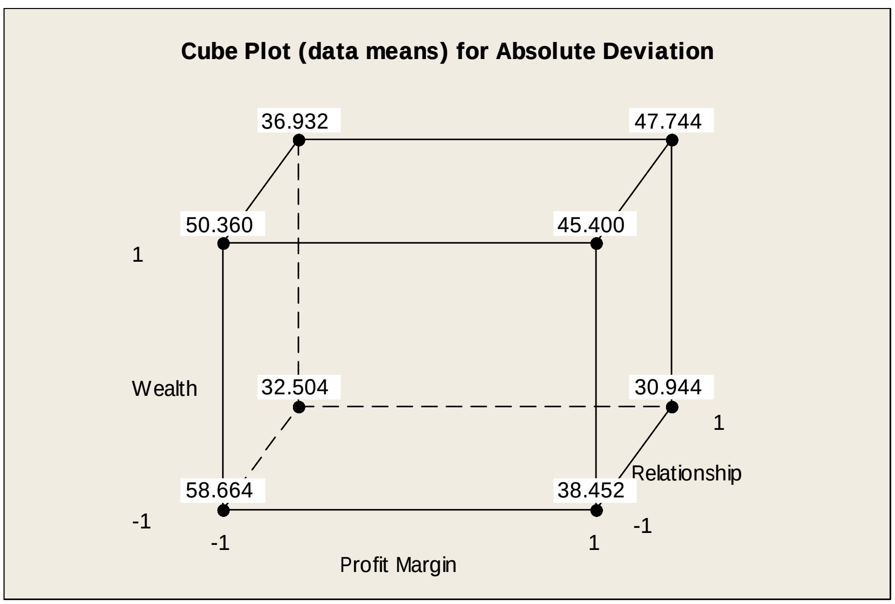

Figure 48: Exp. III Cube Plot for Absolute Deviation of Supplier OQ from Demand

Figure 48 shows the cube plot of the average absolute deviation of supplier's order quantity from retailer's demand under all treatment combinations. The effect of the relationship term is significant under all treatment combinations of NV's initial wealth term and the item profit margin term except when the NV's initial wealth is high and item profit margin is high. The suppliers benefit from a tight relationship with the retailers, as indicated by the lower deviation number when the relationship with retailer is tight. The high initial wealth high profit margin condition has the highest average order quantity among all treatment conditions. This result seems to suggest that higher demand from retailers is more unpredictable for the suppliers. This analysis confirms the tighter relationship between supplier and retailer improves supplier's decision-making.

Table 28: Absolute Deviation from Demand across Different Relationship Factors

	R+	**R-**
Retailers	83.2	89.0
Suppliers	37.8	48.2

Table 28 compares the magnitude of the absolute deviation from demand for the suppliers and for the retailers. For these subjects, a *t*-test analysis on the absolute deviation of retailer's order quantity from demand under different relationship treatment levels was not significantly different (p-value = 0.371). It is not surprising that this result should purport that the relationship term does not affect the quality of retailer's decision making in terms of the absolute deviation from demand because the retailers are conditioned in the same way in both relationship treatment conditions. The absolute deviation of R+ suppliers' order quantity from demand was significantly lower than the absolute deviation of R- suppliers' order quantity from demand (p-value < 0.01). This result reveals the demand information in the tight relationship is more valuable to the suppliers than the demand information in the loose relationship.

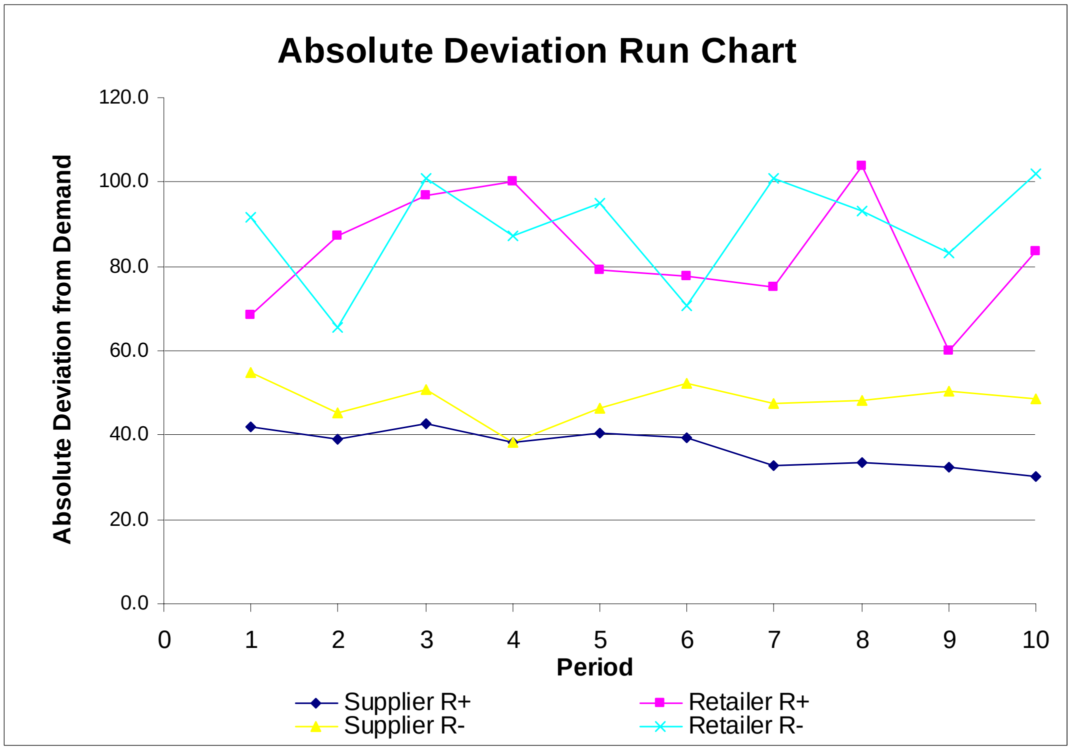

Figure 49: Absolute Deviation from Demand Run Chart

Figure 49 plots the average of the absolute deviation of the supplier and retailer's order quantities from demand over time under different relationship terms. Each data point represents the aggregate value over the initial wealth and the item profit margin terms. The absolute deviation between the retailer's order quantity and demand fluctuates over time with high oscillation under both relationship terms. The absolute deviation of the supplier's order quantity from demand under a loose relationship (R-) is unaffected by more experience of dealing with random retailers. However, the suppliers under tight relationship with the retailers (R+) have lower absolute deviation from the retailers' demand.

Table 29 compares the absolute deviation of supplier's order quantity from demand under the same relationship treatment levels across different run orders. The deviation of tight relationship treatment (R+) the supplier's order quantity from demand was not statistically different across different run orders. On the other hand, under loose relationship treatment, the deviation of the order quantities of the suppliers who had previously faced tight relationship treatment from demand was significantly less than the deviation of the order quantities of the suppliers who had not previously faced a tight relationship treatment (p-value < 0.001). The supplier subjects who began the game under loose relationship had the largest deviation from demand (p-value < 0.001). This result suggests the significance of run order and the benefit of experience for the suppliers in going through tight relationship first for these subjects.

Table 29: Absolute Deviation of Supplier's OQ from Demand across Different Relationship Factors and Run Orders

	Loose First	Tight First
Supplier (R-)	59.8	40.5
Supplier (R+)	37.1	37.0

6.5.1.3 Retailer's average order quantity

This section investigates the effects of item profit margin and NV initial wealth on the retailer's order quantity under different relationship treatments. Table 30 summarizes the significance of item profit margin and NV's initial wealth terms on newsvendor order quantity. This 2^2 factorial design analysis shows a rather counterintuitive result in that the NV's initial wealth term and the item profit margin term do not affect retailer's order quantities under tight relationship with supplier (R+). This is interesting because these factors are significant in all other treatment conditions, both in the single NV setting and in the multi-echelon NV setting. Two explanations to this finding are proposed.

Table 30: Exp. III Effect of Item Profit Margin and Initial Wealth Terms

	Tight Relationship		**Loose Relationship**	
	Wealth	**Profit Margin**	**Wealth**	**Profit Margin**
Supplier	*p<0.01*	*p<0.001*	*p<0.001*	*p<0.001*
Retailer	*n.s*	*n.s*	*p<0.001*	*p<0.001*

First, the retailers purposely use an unpredictable ordering policy to sabotage the supplier's profit. The supporting evidence for this conjecture is that the retailer's behavior results in a 14.4% loss of the supplier's profit. The opposing evidence to this conjecture is that the retailers themselves suffer an even greater loss of 25.6% in their profit. Further analysis reveals an insignificant difference in the variation of individual retailer's order quantities between these two relationship conditions which suggests no evidence of an erratic retailer's order policy under a tight relationship.

Second, a substantial number of retailers exhibit the risk-seeking behavior after loss, previously found in the low profit margin high initial wealth condition (C+W+) in the single NV setting (Experiment I), and these significantly higher than EOQ order quantities blur the characteristics of the overall order quantities. The risk-seeking after loss behavior is most apparent in the low profit margin low initial wealth condition as indicated in Figure 50. This figure shows that the order quantity of the subjects with wealth < 0 is increasing with more losses. The first period consumer demand for this treatment was very low and that was the cause for bankrupting 35% of retailer subjects. What happened next to these bankrupt retailers? 25% of them ordered about 118 units on average and managed to end up in the positive. The remaining 75% suffered even more losses as they continued to be risk-seekers with an average order quantity of more than 165 units. By comparison, subjects who escaped the initial demand shock had an average order quantity of 97.8 units. This unusually high order quantity and high number of subjects with risk-seeking after loss behavior blurred the significance of the main effects. This result indicates that demand shock compounded by bankruptcy-aversion significantly impacts the retailer's decision-making.

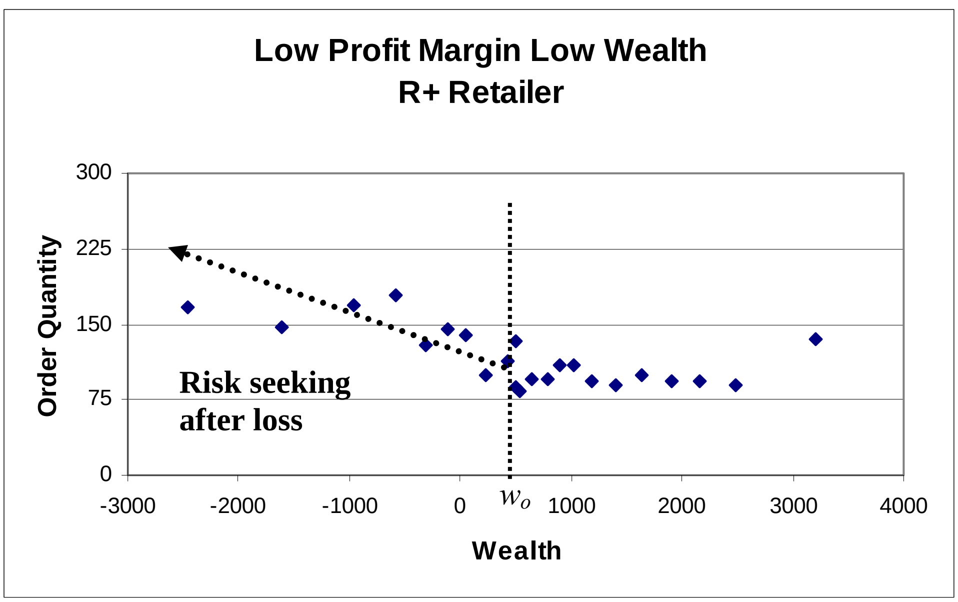

Figure 50: Risk-seeking over Loss in (R+) NV Retailer

6.5.2 Analysis of NV Supply Chain Performance

This Section discusses the impact of the human decision bias and the relationship between supplier and retailer on NV supply chain performance. This research measures the performance of this NV supply chain by its profit and by its opportunity cost.

6.5.2.1 NV supply chain profit

This Section compares the average profit of the NV retailers and the average profit of the NV suppliers. These agents face similar NV investment opportunities under different relationship treatment levels. This research will compare the gap between their average profits and the rationing of the total SC profit between these NV agents. Table 31 indicates that the average profit gap between supplier and retailer in this multi-echelon NV supply chain, defined as $\frac{\text{Supplier's profit - Retailer's profit}}{\text{Retailer's profit}}$, is 16.5% ($p$-value <0.01). Suppliers under a tight relationship treatment conditions had an average profit of 25.7% more than the retailers (*p-value* < 0.05). Suppliers under a loose relationship treatment conditions had an average profit of 9.6% more than the retailers (p-value = n.s.). This result implies that supplier's decision-making is assisted by a tighter relationship with the retailers.

Table 31: Profit Gap across Different Relationship Factors

	Profit Gap
R+	25.7%[1]
R-	9.6%
Overall	16.5%[1]

([1] significant at 95%)

Finally, the average profit for suppliers under tight relationship is significantly lower than the average profit for suppliers under loose relationship (p-value < 0.05), because the average demand of (R+) retailers is lower than the average demand of (R-) retailers. The difference in the retailers order quantity under different relationship conditions is caused the difference in the computer generated consumer demand. The average consumer demand in R+ of 166.9 was higher than the average consumer demand in R- of 147.1 (p-value < 0.05). Due to demand chasing heuristics, R- retailers ordered more than R+ retailers. However, the comparison of supplier's overall profit and the theoretical EOQ profit shows that the suppliers under R+ are achieving better performance because their profit is closer to the theoretical optimal profit.

6.5.2.2 Opportunity cost in NV supply chain

This Section measures the opportunity cost due to the human decision bias in this NV supply chain experiment.

A one-sample t-test shows that the total supply chain profit with theoretical EOQ procurement policy is 63.4% greater than the total supply chain profit in this NV game with HDB (p-value < 0.05). This result rejects the null hypothesis 6.1 which states

$$H_o : \sum_{i=1}^{n} \pi_i^{HDB} \geq \sum_{i=1}^{n} \pi_i^{EOQ}$$
$$H_1 : \sum_{i=1}^{n} \pi_i^{HDB} < \sum_{i=1}^{n} \pi_i^{EOQ}$$

We conclude with 95% that the total profit of supply chain with human decision bias is less than the theoretical profit using EOQ policy.

Further, if retailers retain their decision bias but share their procurement policies with the suppliers, then the total supply chain profit would have increased by 22.3%. Therefore, if the uncooperative supply chain cost is excluded, the loss in profit due to the human decision bias in newsvendor supply chain system is about 25.6%. Current research in the area of improving the cooperation and the information sharing of SC players is certainly justified by this empirical result. In the same way, we argue that human decision bias also deserves more research attention.

This empirical result suggests that a tight relationship between suppliers and retailers in a NV supply chain improves the profitability for the suppliers in terms of the share of supply chain profit. Profit analysis further reveals that the total NV supply chain profit hinges firmly on the retailer's procurement policy. Furthermore, the performance of a NV supply chain can be improved by the reduction of the human decision bias in the single newsvendor setting.

6.5.3 Bullwhip Effect in NV Supply Chain

This Section compares the variability of order quantities of suppliers, of retailers, and of the consumer in 2-echelon newsvendor supply chain under different relationship levels.

Table 32: Exp. III Standard Deviation of Order Quantity

Treatment Conditions	**Supplier**	**Retailer**	**Consumer**[1]
R+	46.61	49.03	86.39
R-	47.91	52.49	93.49
ALL	**48.29**	**51.07**	**90.48**

([1] Consumer demand is a randomly generated number)

Table 32 presents the summary of standard deviation of the order quantities of different players in the supply chains. A two-sample *F* test result indicates the following condition (*p*-value < 0.025):

Var(Supplier (ALL))<Var(Retailer(ALL))<Var(Consumer(ALL))

The two-sample *F* tests for different relationship treatments indicate:

- Var(Supplier (R+))<Var(Retailer (R+)) (*p*-value < 0.125)
- Var(Retailer (R+))<Var(Consumer (R+)) (*p*-value < 0.001)
- Var(Supplier (R-))<Var(Retailer (R-)) (*p*-value < 0.01)
- Var(Retailer (R-))<Var(Consumer (R-)) (*p*-value < 0.001)

Empirical evidence indicates that the "Bullwhip Effect", empirically found in the supply chain of non-perishable products, does not exist in this multi-echelon newsvendor supply chain. On the contrary, the variation seems to be decreasing upstream in the NV supply chain.

This phenomenon can be attributed to the reduction of behavioral causes of the "Bullwhip Effect". A behavioral cause of the "Bullwhip Effect" is the misjudgment of the pipeline inventory by the downstream agents (Sterman, 1989). Our experiment is set up in with the assumption of no lead time and no carrying of inventory, and therefore this behavioral cause of the "Bullwhip Effect" is eliminated in this NV supply chain.

While early empirical data from this experiment does not deny the existence of a reversed "Bullwhip Effect" in NV supply chain, more can be learned about this effect in a "Newspaper Distribution Game". This novel experiment will be different from the "Beer Distribution Game". First, the NV products can not be carried over from one period to another. Second, independent variables commonplace in the classic "Beer Distribution

Game" such as lead time, consumer demand distribution, and information sharing can be added to the list of factors such as item profit margin, supplier-retailer relationship, and NV's initial wealth considered in this research. Finally, contract negotiation between suppliers and retailers can be established by the subjects in this NV game to reflect reality of NV supply chain.

6.5.4 MEHDB Model Fits

Standard tests of multivariable linear regression model, similar to ones used in the single NV setting in Chapter 5.2, validate the goodness of the MEHDB models under both relationship conditions. Table 33 presents a summary of significant coefficients in the MEHDB model under different relationship treatment conditions.

Table 33: Supplier's MEHDB Regression Model Fits under Various Relationship Factors

MEHDB Parameter	R+	R-
p_e^S	0.055*	0.100*
p_u^S	0.050	0.046*
p_d^S	0.455*	0.151*
p_q^S	0.420*	0.706*

(* Significant at 90%)

Regression analysis results are as follows:

1. The effect of anchoring at the previous order quantities remains strong under both relationship conditions. This is consistent to the previous analysis in the single NV setting. This result suggests that the previous order quantity remains a strong predictor of NV subject's next order quantity.

2. The EOQ procurement policy is not as dominant for the suppliers in this multi-echelon setting as in the single NV setting. Suppliers under R+ do not even rely on the EOQ procurement policy. This result indicates the NV suppliers have higher human decision bias than the single NV because the deviation from the classical optimal solutions is greater here.
3. The effect of chasing retailer's demand heuristics is significant in the multi-echelon NV supply chain. Suppliers under R+ actually prefer demand chasing heuristics more than any other procurement policy. Previous single NV result indicates insignificant demand chasing heuristics. Hence, subjects seem more confident in adjustment towards the human generated demand (from retailers) than towards the more random computer generated demand (from consumers).

6.5.5 Trends in Supplier's Preferences on Various NV Requisition Policies

This Section presents the trends of supplier's preference on different procurement policies in the MEHDB model over time. The MEHDB model can be applied to check if subjects exhibited trend in terms of their reliance on different variables in the model. The MEHDB regression model fit the supplier's order quantities up to period t for all t between 3 and 9.

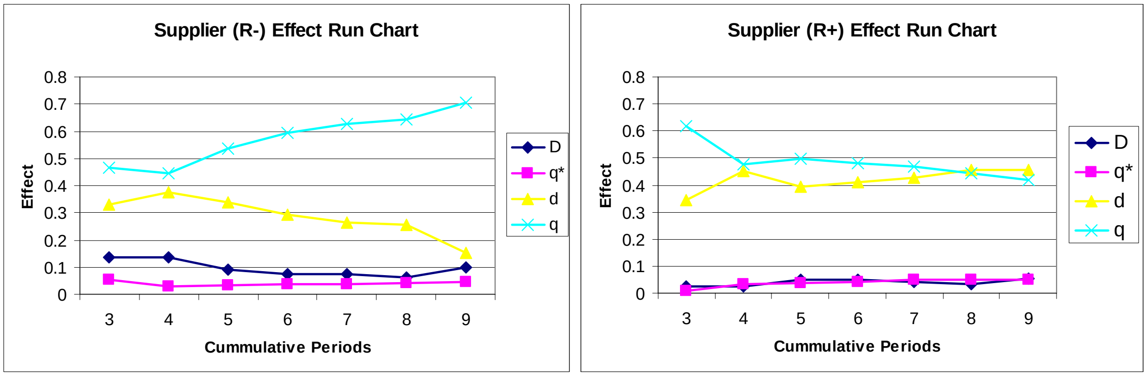

Figure 51: Supplier's MEHDB Effect Run Charts

Figure 51 presents the effect run charts for suppliers under different relationship treatment conditions and no significant trends in subject's reliance on EOQ or average demand procurement policies.

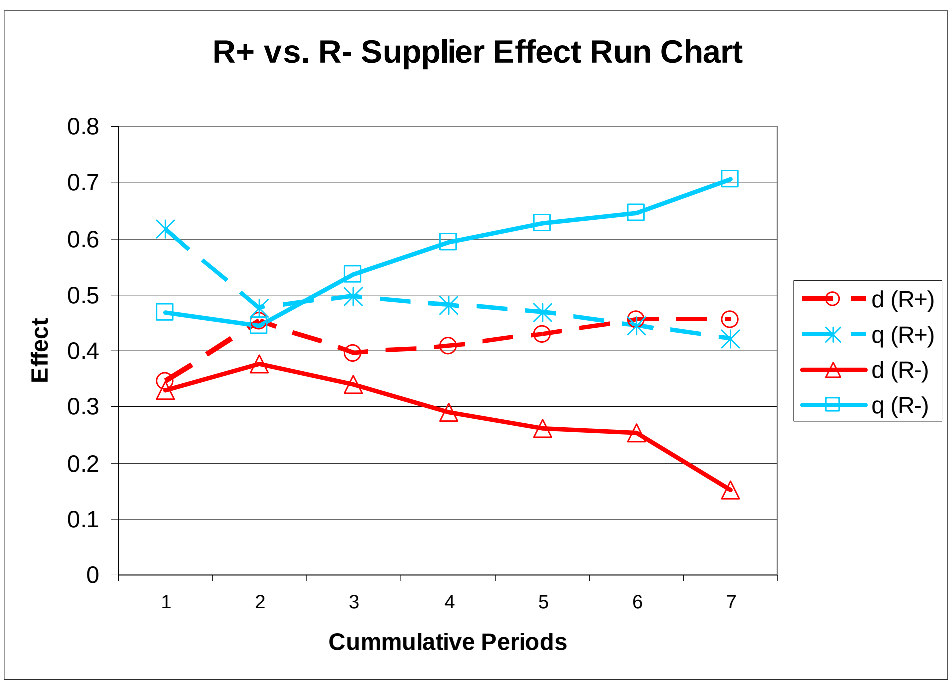

Figure 52: Comparison of Trends in Supplier's MEHDB Effects

Significant trends exist in a supplier's preference to previous order quantity and demand chasing heuristics. Figure 52 plots the effect coefficient of supplier's reliance on previous order quantity and chasing retailer's demand under various relationship conditions. This figure shows an increasing trend in *d (R+)* over time. This trend means that the suppliers under a tight relationship (R+) are relying more on the demand chasing heuristics and are ordering progressively closer to the retailers' demand from previous periods. These suppliers (R+) increase reliance on the retailer's previous order quantity as forecast for future demand from the same retailer. As a result, these suppliers (R+) are relying less on the anchoring at the previous order quantity policy.

The opposite trends are observed by retailers under a loose relationship (R-). Figure 52 shows an increasing trend in *q (R-)* over time and a decreasing trend in *d (R-)*. This implies the suppliers under a loose relationship (R-) prefer to anchor on the previous order quantity over the course of time. These suppliers (R-) rely less on the retailer's previous order quantity.

These analyses reject the null Hypothesis 6.2 which states

$$H_o : p_d^{S(R+)} \leq p_d^{S(R-)}$$
$$H_1 : p_d^{S(R+)} > p_d^{S(R-)}$$

and conclude with 95% that R+ suppliers relied more on retailers' demand than R- suppliers.

6.6 Experiment III Conclusion

This Section concludes the empirical study on this multi-echelon NV supply chain experiment. Figure 53 shows that supplier's average order quantities systematically deviate from the profit maximizing order quantities (EOQ). This result confirms human decision bias exists in this multi-echelon NV system for these subjects.

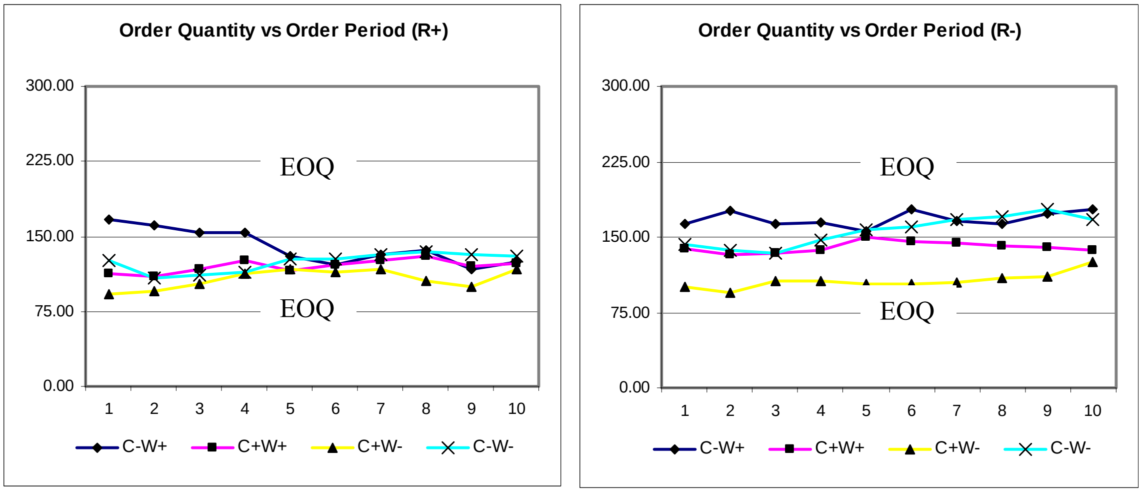

Figure 53: Exp. III Supplier's Average Order Quantity vs. Order Period

The relationship between suppliers and retailers empirically shows improvement to the supplier's decision making in terms of proportion of total supply chain profit for the suppliers. The MEHDB model shows an interesting trend in the supplier's preference on different procurement policies over time. Suppliers under a tight relationship with retailers show increasingly more reliance on a retailer's order quantity to determine their next order quantity. Suppliers under a loose relationship with retailers show preference to anchoring their decision on their own previous order quantity. This empirical result indicates that supplier subjects who deal with the same retailer subjects become more confident in using demand from the retailer to forecast subsequent demand.

The MEHDB model fit for the supplier's order quantity indicates a significant chasing retailer's demand heuristics in these supplier subjects under both relationship treatment conditions. This is a reversal from the result obtained in the single NV setting, where demand chasing heuristics were not significant. This indicates that human-to-human interaction between supplier and retailer is different from the human-to-computer interaction between retailer and the consumer. The computer generated demand is less predictable than the human decision.

The risk-seeking preference under loss, when it persists over longer ordering period and substantiated by large proportion of NV subjects, can blur the impact of well established main effects such as the item profit margin and NV's initial wealth. This behavior, consistent with Prospect Theory, is most apparent for the low profit margin condition. The impact of this behavior may be crystallized in a longer experiment, when the desire to "make up for losses" conceived a risk-seeking behavior. Some subjects under the high initial wealth and low profit margin condition actually ordered at a level of negative expected profit.

A reversed "Bullwhip Effect" is evident in this multi-echelon NV system. Analysis of the variations at different levels of this NV supply chain indicates the variation of order quantity decreases upstream in the NV supply chain. The most significant reduction of variance is between the consumer's order quantity and the retailers' order quantity. This reversed "Bullwhip Effect" can be attributed to the fact that the no lead time and the no inventory holding assumption in the NV system reduces the some sources of the "Bullwhip Effect".

CHAPTER 7: CASE STUDIES OF HUMAN DECISION BIAS AND THE DESIGN OF NEWSVENDOR SYSTEMS

This Chapter illustrates the impact of human decision bias on the performance of a newsvendor (NV) supply chain system. Empirical results of both the single NV experiment and the multi-echelon NV supply chain experiment have shown that human decision in NV systems to systematically deviate from theoretical model solutions. Two NV case studies in this chapter illustrate the impact of various HDB assumptions on their optimal solutions. Due to its significant impact on the performance of NV systems, this chapter makes a case that human decision bias should be included in NV supply chain design models.

7.1 S-D Network Problem

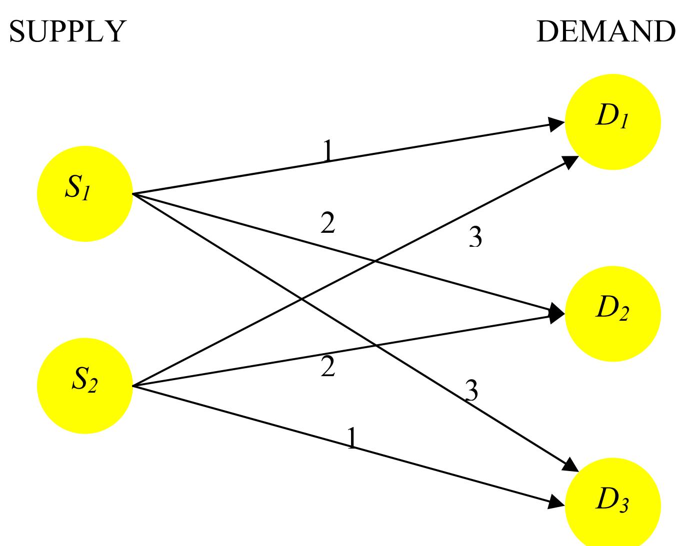

Figure 54: 2S3D Network Problem

Consider a simple Supply-Demand (S-D) network problem with 2 supply nodes and 3 demand nodes as depicted by Figure 54. The problem objective is to minimize the total cost of satisfying demand at demand node *j*, which is uniformly distributed between 0 and 300. Each supply node *i*, when activated, will incur fixed costs of 2100 and 1900 per order period respectively. Notice that the unit transportation cost, given as arc labels, is structured in such a way that the optimal solution will only include one supply node because the maximum transportation cost of 300*(1+2+3) = 1800 is less than the minimum cost of an additional location of 1900.

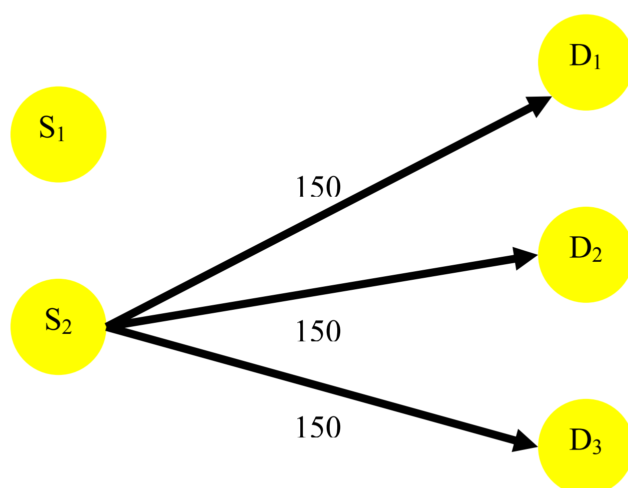

Figure 55: Solution to 2S3D Network Problem with Expected Demand Assumption

There are at least two ways to deal with the stochastic demand. One approach is to use the expected demand of 150 for each node D_j, which will results in an optimal solution of using only supply node, S_2 to satisfy demand at all 3 demand nodes as shown by Figure 55. The total cost for this solution is 1900+150*(1+2+3) = 2800. Another approach is to simulate the demand at each node, D_j and solve the resulting deterministic network problem for many runs to get the best solution of this stochastic problem. We simulated 30 instances for this problem to illustrate this solution technique. The result of each instance is shown in Table 34. Supply node, S_1 is chosen 23% of the time, while S_2 is chosen 77% of the time. Therefore, the optimal solution to minimize total expected cost of satisfying demand at nodes D_1, D_2, and D_3 is S_2.

Table 34: Simulation Results of 2S3D Problem

	Demand Uniform(0,300)			Total Cost		Choice	
Instance	**D1**	**D2**	**D3**	**S1**	**S2**	**S1 Yes**	**S2 Yes**
1	68	167	245	3237	2683	0	1
2	247	83	263	3302	3070	0	1
3	129	125	72	2695	2609	0	1
4	242	232	219	3463	3309	0	1
5	202	1	84	2556	2592	1	0
6	285	204	281	3636	3444	0	1
7	105	66	277	3168	2624	0	1
8	140	120	93	2759	2653	0	1
9	282	38	183	3007	3005	0	1
10	190	152	40	2714	2814	1	0
11	114	196	120	2966	2754	0	1
12	30	266	135	3067	2657	0	1
13	172	263	182	3344	3124	0	1
14	240	126	26	2670	2898	1	0
15	114	254	175	3247	2925	0	1
16	297	45	163	2976	3044	1	0
17	170	171	194	3194	2946	0	1
18	195	191	35	2782	2902	1	0
19	86	164	93	2793	2579	0	1
20	5	90	276	3113	2371	0	1
21	189	264	187	3378	3182	0	1
22	93	40	234	2975	2493	0	1
23	232	290	257	3683	3433	0	1
24	2	32	80	2406	2050	0	1
25	146	16	233	2977	2603	0	1
26	88	13	290	3084	2480	0	1
27	250	11	89	2639	2761	1	0
28	96	50	225	2971	2513	0	1
29	253	30	186	2971	2905	0	1
30	262	217	86	3054	3206	1	0

Consider this 2S3D problem as a newsvendor problem with different cost structures in each of the demand nodes. For example, let us assume that the item profit margin for nodes D_1 and D_2 is 0.75 and the item profit margin for node D_3 is 0.25, then the EOQ is 225 units for nodes D_1 and D_2 and 75 units for node D_3. The cost of using only supply node, S_1 to satisfy demand at all 3 demand nodes = 2100 + 225*(1+2) + 75*3 = 3000. The cost of using only supply node, S_2 to satisfy demand at all 3 demand nodes = 1900 + 225*(3+2) + 75*1 = 3100. Therefore, the optimal solution is obtained by using only supply node, S_1 to satisfy demand at all 3 demand nodes as shown in Figure 56 (a).

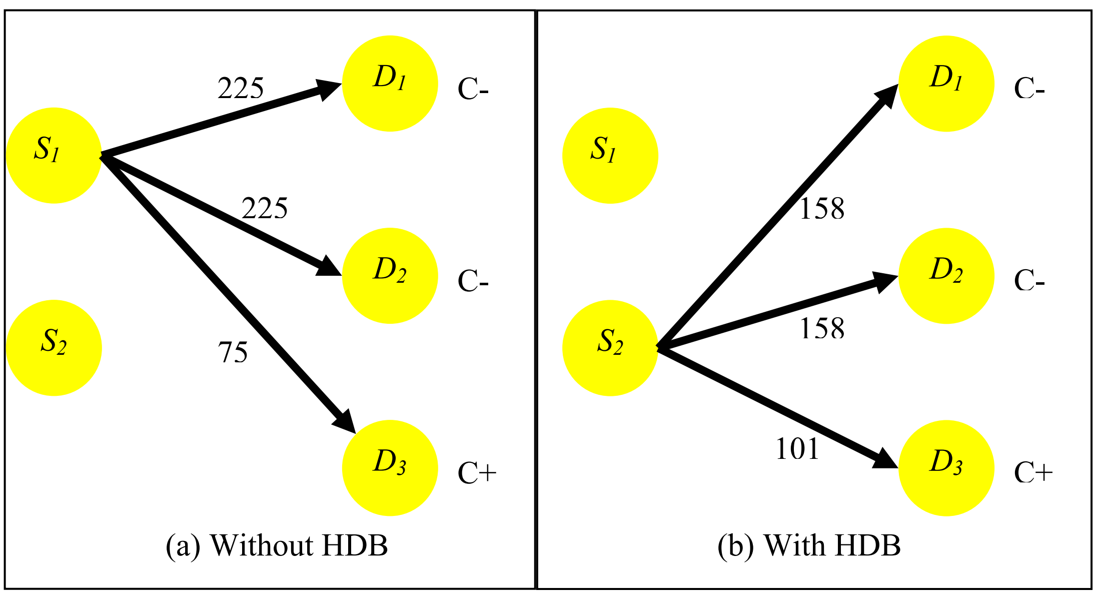

Figure 56: Solutions to 2S3D Newsvendor Network Problem

Another supply chain modeler may consider retailers to exhibit human decision bias. Using the empirical data collected in Experiment I (Chapter 5), SC modeler calculates the average order quantities of the high profit margin item and the low profit margin item to be 158 units and 101 units respectively. The cost of using only supply node, S_1 to satisfy demand at all 3 demand nodes = 2100 + 158*(1+2) + 101*3 = 2877. The cost of using only supply node, S_2 to satisfy demand at all 3 demand nodes = 1900 + 158*(3+2) + 101*1 = 2791. Therefore, the optimal solution is obtained by selecting supply node, S_2 to satisfy demand at all 3 demand nodes as shown by Figure 56 (b).

Table 35: Solutions of 2S3D NV Network Problem under Different Scenarios

Scenario	Optimal Location	Total Cost
EOQ	S1	3000
HDB	S2	2791

Table 35 presents the summary of the optimal solutions to this simple 2S3D network problem with and without the HDB assumption. If this network problem is solved without considering the HDB, then the total cost will be 2100 + 158*(1+2) + 101*3 = 2877, which is 86 more than the total of the optimal solution considering the HDB. The result illustrates how the human decision bias can change the optimal solution to a stochastic S-D network problem.

7.2 Supply Chain Design with Human Decision Bias: A Case Study

The case study in this Section illustrates how HDB can impact the performance of a NV supply chain system if the SC modeler does not account for such bias.

Consider an organic tofu manufacturer, SoyEZ who seeks to set up a food processing operation in one of 25 major metropolitan areas in US where half of the US population resides (Figure 57). The demand for organic food in US, an estimated $14.5

billion industry, is growing at an annual rate of 20-24% and is the fastest growing segment of food industry according to the Organic Trade Association (www.ota.com).

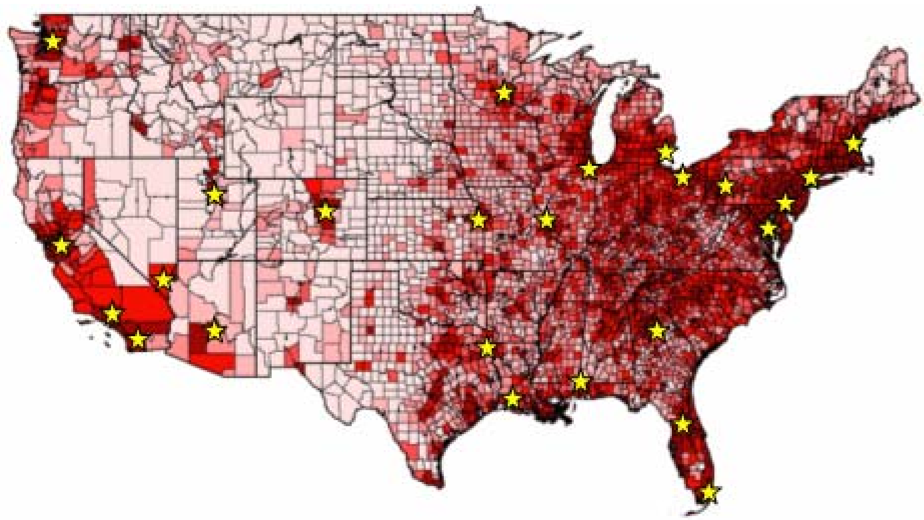

Figure 57: Map of Major US Metropolitans

Some drawbacks to this new product are the highly unpredictable demand and the short shelf life. The demand of this new product in each metropolitan area, j can only be assumed to be uniformly distributed between [0, 2*D_j], where D_j, the average demand, is proportional to the population at location j. Due to the short shelf life, the delivery of this fresh produce must be expedited if the traveling distance is more than 1500 miles. Therefore, the retailers outside of the 1500 miles radius have to pay a premium cost of \$90 and those within 1500 miles from the selected manufacturing location pay \$30 per unit. The MSRP of this organic tofu in all metropolitan areas is set at \$120 per unit. SoyEZ assumes all cost to deliver products to the retailers. This fixation of retail price is commonplace in the fresh produce industry (Chalfant et al., 2003). The logistics cost structure includes a fixed cost of \$300,000 and a transportation cost proportional to the distance between the wholesale location and the retailer's location.

This single location selection problem for the supplier can be formulated as the following deterministic mix integer program:

$$\text{Min} \sum_{i=1}^{25}\sum_{j=1}^{25} c_{ij}x_{ij} + \sum_{i=1}^{25} f_i y_i$$

Such that

$$\sum_{i=1}^{25} x_{ij} \geq d_j \quad \forall j$$

$$\sum_{j=1}^{25} x_{ij} \leq M y_i \quad \forall i$$

$$\sum_{i=1}^{25} y_i = 1$$

y_i : binary

Where

i:	The set of supply nodes.
j:	The set of demand nodes.
x_{ij}:	The decision variable of the amount of product to ship from i to j.
y_i:	The decision variable of selecting to set up distribution in location i.
c_{ij}:	The unit cost to ship product from i to j.
f_i:	The fixed cost to operate at location i.
d_i:	The demand at location j.
M:	A (big M) constant value greater than the maximum demand at any node j.

This single location selection problem under uncertainty is commonly solved in one of these ways. The first method is to solve the problem deterministically by assuming fixed demands at each node. Some reasonable fixed demand values are the expected demand or the EOQ for NV type products. Another method is to simulate multiple instances of the deterministic problem and compile the solutions to select the best option. This technique was used to solve the 2S3D network problem earlier. For this single location selection problem the expected demand method and the simulation method yield the same result.

The human decision bias found in the NV decision-making can be modeled in this location selection problem under uncertainty. A NV retailer with a bias parameter, b when presented with item profit margin, m will order at $(m-(m-0.5)b)*2D$. For example, consider a low profit margin (m=0.25) and a high profit margin (m=0.75) NV investment options whose demand is Uniform [0,100]. A slightly bias newsvendor (b=0.1) when faced with this NV investment opportunity will order (0.25-(0.25-0.5)*0.1)*100=27.5 at the low profit margin condition and (0.75-(0.75-0.5)*0.1)*100=72.5 at the high profit margin condition. Another newsvendor with b = 1 will order 50 units at both the low profit margin and the high profit margin conditions.

Table 36: Fresh Produce Location Solution Summary

	EOQ	Average	Slight (b=0.1)	High (b=0.5)	2E	2E R+	2E R-
Location	Washington	Las Vegas	New York	LA	LA	LA	LA
Profit	$ 126,796	$183,930	$120,583	$143,820	$108,045	$100,435	$115,695

The bias parameter, *b* and the normalized human decision bias data from the multi-echelon NV supply chain experiment are used to generate different scenarios of retailer's behaviors. Table 36 shows the optimal location and optimal profit for SoyEZ under various assumptions of retailer's behaviors. For example, if the retailers are assumed to order at the EOQ of the classic NV solution then SoyEZ should locate its operation at Washington DC for a maximum expected profit of $126,796. However, if retailers are assumed to order the mean demand then SoyEZ should locate its operation at Las Vegas for a maximum expected profit of $183,930. If retailers exhibit decision bias proportional to the empirical results of multi-echelon NV experiment (2E), then the optimal location will be Los Angeles with an expected profit of $108,045. Similarly, if the relationship between the suppliers and the retailers are tight (2E R+) or loose (2E R-), then the expected profit will be $100,435 and $115,695 respectively. It is clear from this example that the optimal solution of this location selection problem depends largely on the various assumptions of the HDB.

Table 37: What-if Analysis on the Impacts of Assuming no Human Decision Bias

	Outcome						
Washington, DC	EOQ	Average	Slight (*b*=0.1)	High (*b*=0.5)	2E	2E R+	2E R-
Loss in Profit	0	-66.6%	-0.3%	-34.6%	-76.3%	-91.4%	-63.2%

What if the SoyEZ makes a wrong assumption about the demand?

Case 1: SoyEZ assumes the retailers will follow the EOQ from the classical newsvendor solution in placing their orders and sets up its operation at Washington, DC. Table 37 summarizes the percentage of loss in profit for the supplier due to different scenarios of HDB. If the retailers indeed order at EOQ then the loss in profit is zero. However, if retailers order at high level of human decision bias (*b*=0.5), then SoyEZ will make 34.6% less than the optimal profit had the location been set in Los Angeles. The greatest loss in profit is found in the situation where the retailers and suppliers had tight relationship, which is perhaps the most likely situation since there is only one supplier of this organic tofu.

Table 38: What-if Analysis on the Impacts of Assuming Average Order Quantity

	Outcome						
Las Vegas	EOQ	Average	Slight (*b*=0.1)	High (*b*=0.5)	2E	2E R+	2E R-
Profit Difference	-49.0%	0%	-36.4%	-13.6%	-16.3%	-0.2%	-19.5%

Case 2: The retailers are assumed to order at the average demand level, and the wholesaler places its operation at Las Vegas. Table 38 summarizes the percentage of loss in profit for the supplier due to different scenarios of HDB. For example, if retailers order at high level of human decision bias (*b*=0.5), then SoyEZ will make 13.6% less than the optimal profit had the location been set in Los Angeles. Comparing the overall scenario outcomes in Table 37 and Table 38, we observed the assumption of average demand to be more robust than the assumption of classic newsvendor solution.

CHAPTER 8: CONCLUSION AND FUTURE RESEARCH

This Chapter summarizes major findings of this research and proposes future research ideas. This research is motivated by the recent discovery of human decision bias in the classical NV problem and the potential impacts of this bias on the performance of NV systems. Current empirical results describe NV decision-making to be inconsistent with risk-seeking, risk-aversion, Prospect Theory, and other utility models (Schweitzer and Cachon, 2000). Enhancement of the feedback to the decision-makers in another NV empirical study improves NV decision-making but fails to eliminate human decision bias (Bolton and Katok, 2004). These empirical results focus on alternating levels of item profit margins to study NV decision-making.

This research purports to explore additional factors influencing NV decision-making and purposes a human decision bias (HDB) model as a framework to describe and compare NV decision-making under alternative conditions. Single and multiple NV experiments were set up to test the significance of decision-maker's initial wealth, item profit margin, item salvage value, NV training, and the interaction between supplier and retailer. A total of 171 student subjects were recruited to participate in various NV experiments. Empirical data from these experiments are fitted on the HDB regression model to distinguish most prominent NV procurement policies. Business case studies were set up to illustrate the impact of human decision bias on the performance of NV systems.

This research is not without its limitations. First, the human decision bias (HDB) regression model can only ascertain the relationship between NV decision-making and various predestined theoretical NV procurement policies. However, we will not know the underlying causal mechanism of NV decision-making process precisely because there may be alternative causal explanations not included in the HDB model. This research chooses the most reasonable independent variables for the HDB model from the empirical and theoretical results of NV decision bias (Schweitzer and Cachon (2000), Bolton and Katok (2004)). Second, the college student subjects may have different objectives from the real-life business managers. Therefore, the empirical evidence found in these experiments may not apply to real life procurement managers in general or students of other disciplines and levels. Third, the anecdotal evidence of the impact of HDB on the optimal solutions of an US organic food network in Chapter 7 should not be perceived as facts without trepidation. The dearth of real data in the fresh produce market has limited the case study to truly reflect reality of this industry. Finally, this research assumes no contractual agreement between the suppliers and the retailers of the NV supply chain. The complexity of the contracts between suppliers and retailers, which are commonplace in real life supply chain, are beyond the scope of this research.

The major results are separated into 2 sections. The first section describes the empirical results from various NV experiments and the second section describes the relationship between human decision bias and NV system design. Future research ideas are presented last.

8.1 Bias in the Newsvendor Decision-Making

This Section presents major empirical results of the single and the multi-echelon newsvendor (NV) experiments.

1. This research validates the existence of human decision bias in NV system. The order quantity of the newsvendor decision-makers in single and multi-echelon NV settings systematically deviate from the profit maximizing order quantities. The subjects ordered too high for low profit margin condition and ordered too little for the high profit margin condition.
2. The NV initial wealth significantly influences NV decision making. Subjects with higher initial wealth order more than subjects with lower initial wealth under the low profit margin condition. The impact of this NV preference is quite far reaching. Wealthier NV subjects are found to exhibit a risk-seeking behavior after suffering losses in the NV experiment. Empirical data from the multi-echelon NV experiments show more experienced NV retailer subjects order at a level which has expected profit less than zero. This investment option likens to the acceptance of a risky gamble with negative expected payoff.
3. The item salvage value does not significantly affect NV decision-making when the item profit margin does not change. Empirical results show NV subjects to be indifferent between NV investment with zero salvage value and NV investment with nonzero salvage value.
4. The theoretical NV training session does not significantly improve newsvendors' decision-making. Subjects who perform very well in the theoretical NV problem exercises continue to exhibit human decision bias in the NV experiment. This

result confirms that student subjects exhibit human decision bias not because they forget the solution to the classical NV problem as suggested by previous NV empirical study (Schweitzer and Cachon, 2000). A major distinction between the theoretical NV exercises and the NV experiments is that there is only one right answer to the classroom exercise and there is no right or wrong answers in the NV experiments. Students in the classroom will answer in such away to pass the test and students in the NV experiment will order as they want without trepidation of failing the test.

5. Decision-makers utilize an anchoring and adjustment heuristics to make NV procurement decision. Subjects tend to anchor at the previous order quantity and adjust according to *posterior* feedbacks. The HDB model demonstrates that the decision-makers relied significantly on their previous order quantity under various NV experimental settings. This result highlights the importance of influencing NV's first order quantity.

6. A reversed "Bullwhip Effect" is evident in the multi-echelon NV supply chain experiment. The empirical analysis of the order quantities of the subjects in the multi-echelon newsvendor experiment demonstrates an upstream diminution of the oscillation of agent's order quantities the supply chain. This research conjectures that the no inventory holding and the no lead time assumptions of the NV supply chain experiments may have reduced the "Bullwhip Effect" commonplace in supply chain of durable products. The reversed "Bullwhip Effect" in the newsvendor supply chain systems implies that the suppliers face less uncertainty in demand than the retailers do. Therefore, the NV suppliers

enjoy higher average profit per unit and higher share of the total supply chain profit than the retailers do. This disparity in the performance of suppliers and retailers is most apparent when the suppliers are dealing with the same retailers over time.

7. Empirical data shows that human decision bias accounts for more than 17% in loss of profit in the single NV setting and a 25% in loss of profit in the multi-echelon NV setting. By definition, any deviation from the optimal NV ordering policy will adversely impacts the profitability of the NV system. This adverse effect is compounded when more NV agents are involved in the multi-echelon NV systems. Empirical results indicate the loss of profit due to human decision bias is significantly more than the loss of profit due to non-cooperation between suppliers and retailers. Improvement to NV decision-making will significantly improve the bottom line of the NV supply chain systems.

8.2 Human Decision Bias and Newsvendor Supply Chain Design

This section discusses how the human decision bias affects the performance of a NV supply chain system and argues for its incorporation in the design of a NV supply chain.

Due to high demand uncertainty of NV type products such as woman's fashion, Halloween customs, and Christmas ornaments, retailers generally desire to order as late as possible, so that they can have better demand forecast. On the other hand, the manufacturers and distributors, with their limited resource, desire more time prior to selling season to plan for production and to avoid excessive overtime charges. This tension exists universally in all supply chain systems (Chen and Xu, 2001).

The impact of the human decision bias on SC performance is most apparent in a situation where all agents of the supply chain are required to set aside resource in advance of the selling season. If suppliers do not have to commit resources before receiving retailer's order, then the impact of human decision bias is limited to the retailer's loss of profit. However, the supply chain tension described above will inevitably cause the suppliers to commit some resources prior to receiving orders from retailers.

Ignoring the human decision bias in NV supply chain system can be costly. Empirical evidence from the NV experiments indicates that human decision bias accounted for more than 25% of loss in total supply chain profit in the multi-echelon NV setting and more than 17% of loss in profit in the single NV setting.

The human decision bias in NV system, classifiable as an error in demand forecast bias, will impact the performance of SC system more adversely than other forecast errors. Lee et al. (1997) show that out of the two types forecasting errors, errors in forecast bias (the mean) has a more significant impact on production system performance than errors in forecast variability (the variance). The HDB, a systematic deviation from various model solutions, fits the description of an error in demand forecast bias.

Some mitigation to the potential problems caused by forecasting errors can be applied to reduce the impact of HDB. Wei et al. (2002) show that early order commitment by retailer can alleviate the impact of forecast error on supply chain performance. The forecasting of consumer demand is quite difficult, but if the retailers provide some initial order quantities prior to the realization of consumer demand, then the supply chain performs better. Byrnes and Shapiro (1992) empirically examined the Bullwhip effect in the medical supply industry which is associated with the error in forecast variability. The investigators implement some fixed order policies in the hospitals, and as the result, the hospitals save substantial cost due to reduction in the storage space requirement. These results indicate that reduction of forecast errors, such as those caused by the HDB, can improve supply chain performance.

The human decision bias needs to be accounted for in supply chain design, not only because of its adverse effects indicated above, but also because it assaults two basic assumptions of the analytical techniques conventionally used to design a SC system under uncertainty. First assumption is that consumer demand is propagated in the SC without any changes and can be used as requirement for all agents in the supply chain. Empirical results from this multi-echelon NV supply chain experiments show that the demand distribution has changed from customers to retailers and from retailers to suppliers in terms of its mean and its variance. Second assumption is that retailers will order according to some very reasonable models, such as the expected demand procurement policy or the classic NV problem procurement policy. Empirical results from this dissertation and others have shown a systematic deviation of decision-maker's order quantities from the expected demand level and profit maximizing EOQ (Schweitzer and Cachon (2000) and Bolton and Katok (2004)).

Case study of US fresh produce supply chain system in Chapter 7 shows the potential problems of ignoring human decision bias. Analysis reveals even slight human decision bias may change the solution of the location selection problem quite dramatically. For example, the optimal location under the expected demand assumption is in the West Coast, and the optimal location under assumption that retailers exhibit slight HDB is in the East coast.

8.3 Research Extensions

This section highlights some future research ideas for individual NV and multi-echelon NV decision-making. The dearth of empirical evidence significantly undermines the validity of the voluminous theoretical research of NV problem, especially when early evidences consistently point to a systematic discrepancy between the empirical and theoretical results.

For further empirical research of single NV decision-making, investigators will investigate if de-biasing methods such as the graphical mapping method (Roy et al., 1996) and the warning method (Block et al., 1991) will improve NV performance. Different treatment conditions of item profit margins such as (p=4, c=1, s=0) and (p=4, c=3, s=0) can be compared to previously tested item profit margins conditions (p=12, c=3, s=0) and (p=12, c=9, s=0) to investigate if changes in the expected profit / order will affect NV decision-making. Finally, longer experiment can be set up to compare NV decision-making in the high cost high initial wealth and the high cost low initial wealth conditions. This experiment will verify if subjects who have suffered loss will behave differently from those who have made profit given the same NV investment option and wealth.

For further empirical research of NV decision-making in the multi-echelon supply chain setting, investigators may consider a "Newspaper Distribution Game" where inventory holding is disallowed at certain levels of the supply chain. This NV game can be set up with various objectives such as maximizing total supply chain profit, maximizing individual NV profit, minimizing total waste, and maximizing customer service. Independent variables commonplace in the classic “Beer Distribution Game” such as lead time, consumer demand distribution, and information sharing can be added to the list of factors such as item profit margin, supplier-retailer relationship, and NV’s initial wealth considered in this research. More dynamic variables commonplace in the fresh produce industry such as contract negotiation between supplier and retailer, multi NV products, and imperfect knowledge about cost and demand may prove to be the most exciting extension of current empirical studies of NV problem. We believe that experiments like these can illuminate the complexity of managing supply chain of newsvendor products and provide suggestions for improving its performance.

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